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Sectoral connectedness: New evidence from US stock market during COVID-19 pandemics

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**ABSTRACT**

We examine volatility connectedness of 11 sectoral indices in the US using daily data from January 01, 2013 to December 31, 2020. We employ the connectedness measures of Diebold and Yilmaz (2009, 2012, 2014), unveiling changes in sectoral connectedness and stylized facts regarding specific sectors during the COVID-19 pandemic. Among several results, we find extraordinary increase in total connectedness, from early stages of international spread to the end of July 2020; some relevant changes in the pairwise connections between sectors, especially among the originally stronger ones. However, in a total net connectedness perspective, there is little evidence of structural changes.

1. Introduction

The COVID-19 appeared in Wuhan, China in December 2019. Initially thought as a pneumonia cluster, it rapidly developed to receive the WHO pandemic status on March 11, 2020. By the end of 2020, there have been more than 83.5 million cases, with 1.8 million deaths in 192 affected countries. In the real economy, the consequences were likewise devastating. According to Goodell (2020), concerns arise from health systems costs, job productivity loss, disrupted economic activity, tourism, and foreign direct investment.

As expected, the spillovers to worldwide financial markets have been considerable. For instance, Baker et al. (2020), comparing the current crisis with other pandemic periods, argue that no disease outbreak, including the Spanish Flu, has impacted the US stock market as forcefully as COVID-19. Ashraf (2020) suggests that stock markets quickly reacted to COVID-19 and that this response depends on the outbreak stage. In this sense, Corbet, Larkin, and Lucey (2020) show that, at earlier stages of COVID-19, Chinese financial markets acted as the epicenter of financial contagion, and Ali et al. (2020) find that while the earlier epicenter China has stabilized, global markets went into freefall.

Still in this literature on pandemic financial impacts, but with an emphasis on volatility, according to Haroon and Rizvi (2020), the COVID-19 outbreak resulted in unprecedented news coverage and the ensuing uncertainty in financial markets lead to heightened volatility. Lyocsa et al. (2020) find that COVID-19 related Google search volume predicts price variations. Sharif et al. (2020) report unprecedented impact of COVID-19 and oil price shocks on stock volatility, while Zhang et al. (2020) show substantial increase in volatility and clearly different patterns of stock markets linkages before and after the pandemic.
Considering its unprecedented nature, COVID-19 pandemic may entail important qualitative changes in the dynamics of financial markets. Therefore, extensive re-examinations of previous findings are occurring. Indeed, it is possible that COVID-19 will alter entire research streams (Yarovaya et al., 2020).

A particularly hot topic during COVID-19 re-examinations has been financial connectedness1. For instance, Amar et al. (2021) examine the spillovers and co-movements among commodity and stock prices major oil-producing and consuming countries. Corbet et al. (2021) study volatility spillovers from Chinese financial markets upon a number of financial assets. Rizwan et al. (2020) analyze systemic risk of banking sectors across the globe. Hernandez et al. (2020) examine the network spillovers, portfolio allocation characteristics and diversification potential of bank returns from developed and emerging America. Akhtaruzzaman et al. (2020) study how financial contagion occurs through financial and nonfinancial firms between China and G7 countries during the COVID-19 period. Matos et al. (2021) study sectoral contagion in the US during COVID-19 besides the impact of the pandemic over the S&P 500. Corbet, Goodell, and Gunnay (2020) examine co-movement and spillovers of oil and renewable firms under the event of negative WTI prices occurred during COVID-19. Fasanya et al. (2020) consider the connectedness between COVID-19 and global foreign exchange markets. Karkowska and Urjasz (2021) examine the connectedness structures of sovereign bond markets in central and eastern Europe.

This interest is justifiable once financial connectedness is of great practical use for a broad audience given its importance to various aspects of risk. Particularly during crisis and turbulent periods as COVID-19 pandemic, various economic agents, including investors and policymakers, can make use of the size and direction of the net spillovers for enhancing portfolio decisions and the formulations of policy to restore and safeguard financial stability (Bouri et al., 2021). For the academic community, studying connectedness at this very moment should be important to better grasp the range of implications of highly stressing moments over the financial markets.

Sectoral connectedness is arguably of similar importance for a large portion of investors and asset managers that deal with national portfolios and for virtually all policy makers. It can also provide different insights to the academic community, once it could signal some internal dynamic that is specific of a given country and would not be completely unveiled using aggregate data. Nevertheless, sectoral connectedness has not received nearly as much attention as studies focusing on aggregated markets, as discussed in Mensi et al. (2020).

More related to our study, regarding sectoral connectedness in the US, Barunik et al (2016) examine asymmetries in volatility spillovers using most liquid stock in seven sectors. They find that spillovers are transmitted at different magnitudes that sizably change over time in different sectors and a substantial connectedness increase during the GFC. Also, Mensi et al. (2020) study volatility connectedness among ten US sectors from 2012 to 2018. They find time-varying spillovers among US sectors which is intensified during economic, energy and geopolitical events.

In this study, we contribute to the literature by examining for the first time how the network of sectoral indices in the US is affected by such an unprecedented turmoil as the COVID-19 pandemic. More specifically, to our knowledge, we are the first to examine the sectoral connectedness among eleven US sectors covering an entire year of COVID-19 pandemic and using Diebold and Yilmaz (2009, 2012, 2014) methodology. We use daily volatility data from January 01, 2013 to December 31, 2020 providing both a relatively tranquil pre-COVID-19 baseline for comparative analysis and an entire year of COVID-19 pandemic data.

The main aim is to examine possible quantitative (levels) and qualitative (roles/directions) changes occurred during COVID-19 as well as to observe stylized facts regarding specific sectors behavior under pandemics context.

Among several results, we find extraordinary increase in total connectedness among US sectoral indices volatility during COVID-19. Furthermore, in the pairwise connections between the sectors, both intensity and directions have presented some relevant changes. Also, we find particularly relevant behavior of specific sectors like Financials and Energy. Our findings encounter practical use for asset managers and policy makers alike.

The remainder of this study is organized as follows. Section 2 delineates the methodology. Section 3 shows the data and a preliminary analysis. Section 4 presents the empirical results. Section 5 contains robustness checks, while Section 6 concludes.

2. Methodology

The core methodology used in this study is the connectedness indices of Diebold and Yilmaz (2009, 2012, 2014). It enables us to fulfill our objectives - highlight both quantitative (levels) as qualitative (roles/directions) changes in sectoral connectedness occurred, as well as any unusual behavior of specific sectors - by means of static and dynamics analysis of the proper connectedness indices.

As discussed in Corbet, Goodell, and Gunnay (2020), this model has a number of advantages, namely, it allows bilateral spillovers unlike the SAMEM model of Otranto (2015), it allows displaying the strength of spillovers and enable proper comparisons among alternative model configurations and variable sets. Regarding concurrent correlation-based methods, as Wavelet analysis and the multivariate GARCH models, we believe the chosen methodology is advantageous because it is able to infer direction of spillovers for a large number of simultaneously interacting variables in a clear and compact manner.

Consider a covariance stationary N-variable VAR(p),

\[ x_t = \sum_{i=1}^{p} \Phi_i x_{t-i} + \sum_{j=0}^{N} D_{ij} I_{N_j} + \epsilon_t, \]

with MA representation \( x_t = \sum_{i=0}^{\infty} A_i \epsilon_{t-i} \), where \( \epsilon \sim (0, \Sigma) \) is a vector of i.i.d. disturbances with covariance matrix \( \Sigma \), \( I_{N_j} \) is the identity matrix, and \( D_j \) are dummy variables that

1 Financial connectedness has been measured using a variety of approaches as dynamic conditional correlation (DCC) of Engle (2002), CoVaR of Adrian and Brunnermeier (2016) and concepts of network topology, being related to terms as spillovers and contagion. In this work we use Diebold and Yilmaz (2009, 2012, 2014) measures. Refer to Diebold and Yilmaz (2015) for a detailed comparison of concurrent approaches.
account for structural breaks\(^2\).

Using the generalized\(^3\) VAR (GVAR) framework of Koop, Pesaran, and Potter (1996) and Pesaran and Shin (1998), the H-step-ahead error variance in forecasting \(x_t\) that are due to shocks in \(x_p\), \(i = 1, 2, \ldots, N\) is computed as:

\[
\theta^H[H] = \frac{\sigma^2_{ij} \sum_{h=0}^{H-1} (c_i \Lambda_h \Sigma c_j)^2}{\sum_{h=0}^{H-1} (c_i \Lambda_h \Sigma c_i)}
\]

where \(\sigma_{ij}\) is the standard deviation of the error for the \(j^{th}\) equation, and \(e_i\) is the selection vector, with one as the \(i^{th}\) element and zeros otherwise. As the shocks in the GVAR framework are not orthogonal, one needs to normalize (1) in the following manner to obtain the generalized forecast error variance shares:

\[
\bar{\theta}^H[H] = \frac{\theta^H[H]}{\sum_{j=1}^{N} \theta^H[H]}
\]

The essential idea of Diebold and Yilmaz (2009, 2012, 2014) is to construct a connectedness table, such as Table 1 in Zhang (2017). From this table, a series of connectedness indices are formed, as follows.

The total connectedness index:

\[
S^H[H] = \frac{\sum_{i=1}^{N} \theta^H[H]}{\sum_{j=1}^{N} \theta^H[H]} \cdot 100 = \frac{\sum_{i=1}^{N} \theta^H[H]}{N} \cdot 100
\] (3)

The directional connectedness from (“from”) all other markets \(j\) to market \(i\):

\[
S^F[H] = \frac{\sum_{j=1, j \neq i}^{N} \theta^H[H]}{\sum_{j=1}^{N} \theta^H[H]} \cdot 100 = \frac{\sum_{j=1, j \neq i}^{N} \theta^H[H]}{N} \cdot 100
\] (4)

The directional connectedness to (“to”) all other markets \(j\) from market \(i\):

\[
S^T[H] = \frac{\sum_{j=1, j \neq i}^{N} \theta^H[H]}{\sum_{j=1}^{N} \theta^H[H]} \cdot 100 = \frac{\sum_{j=1, j \neq i}^{N} \theta^H[H]}{N} \cdot 100
\] (5)

The net (“net”) directional connectedness from market \(i\) to all other markets \(j\):

\[
S^N[H] = S^F[H] - S^T[H]
\] (6)

Finally, the net pairwise connectedness from market \(i\) to market \(j\):

\[
S^P[H] = \left( \frac{\theta^H[H]}{\sum_{j=1}^{N} \theta^H[H]} - \frac{\theta^H[H]}{\sum_{j=1}^{N} \theta^H[H]} \right) \cdot 100 = \left( \frac{\bar{\theta}^H[H] - \bar{\theta}^H[H]}{N} \right) \cdot 100
\] (7)

Regarding parameters setting, we follow Diebold and Yilmaz (2014), using \(p = 3\) for lag structure, \(H=12\) for horizon of underlying variance decomposition and \(W=100\) days for size of overlapping window when computing rolling indices.

3. Data and preliminary analysis

Our sample period is from January 01, 2013 to December 31, 2020, a total of 2015 daily observations. Following Akhtaruzzaman et al. (2020), the starting point was defined so that the pre-COVID-19 period did not overlap the global financial crisis (2007-2009) or the European sovereign debt crisis (2010-2012). The end point was the last available. We assume COVID-19 period begins on December 31, 2019, the day cases of pneumonia\(^4\) detected in Wuhan, China, are first reported to the WHO. This period ends on December 31, 2020, the end of our sample.

The raw data is comprised of daily percent returns of 11 US sectoral indices formed by the companies included in the S&P 500 index and classified as members of each of the sectors under the Global Industry Classification Standard (GICS). Namely, we use the indices

\(^2\) We thank an anonymous reviewer of this journal for suggesting accounting for structural breaks. The original qualitative results, however, have not changed and can be provided from authors upon request.

\(^3\) This approach makes the forecast error variance decomposition invariant to the ordering of variables in the VAR and is used in this study.

\(^4\) At this stage, the virus was still unknown. For a complete list of early COVID-19 key dates see Table 1 of Corbet, Larkin, and Lucey (2020).
S&P 500 Consumer Discretionary (SPLRCD), Consumer Staples (SPLRCS), Energy (SPNY), Financials (SPSY), Health Care (SPXHC), Industrials (SPLRCI), Information Technology (SPLRCT), Materials (SPLRCM), Real Estate (SPLRCREC), Telecom Services (SPLRCL) and Utilities (SPLRCU). The data is provided by Investing.com.

All considered indices are market cap weighted and quarterly rebalanced, implying that the weight of specific companies, and which companies are considered in the indices, evolve along the sample. We understand this fact should not be corrected for, once the data already provides a valid proxy for sectoral performance, the weighted returns of representative stocks at the moment. It should also be noted that this weighting method is usual for broad market indices, and that most empirical literature does not correct for rebalancing.

Fig. 1 show the cumulative and daily returns on the considered indices. In all series, we can see increase in volatility during the COVID-19 period. Particularly, daily maximums and minimums returns occurred during the pandemic for all indices. It is also noteworthy the fact that the March 2020 COVID-19 induced drawdowns have been of greater magnitude than those observed in the much longer pre-COVID-19 period.

We transform the raw data to get the variables of interest, price volatilities. Put in another way, in the present study the vector of variables of interest, $x_t$, represents price volatilities from sectoral indices in the US. As with Antonakakis et al. (2018) and Corbet, Goodell, and Güney (2020), among others, we define\(^6\) the index $i$ price volatility as the absolute return $r_{it} = \ln P_{it} - \ln P_{i,t-1}$, where $P_{it}$ is the closing value of index $i$ price on day $t$. We have detected a few structural breaks in the dataset using CUSUM tests, both on the pre-COVID-19 (Energy, IT and Utilities) and on COVID-19 period (Health care and Staples). Thus, we have included dummy variables in our model to account for these breaks.

Table 2 shows descriptive statistics based on sectoral price volatility from pre-COVID-19 and COVID-19 periods. We highlight that considerable increase of mean volatility is observed across all indices from pre-COVID-19 to COVID-19 period. The same increasing behavior applies to second, third and fourth moments of return volatilities, indicating a pattern of higher levels of dispersion, asymmetry, and kurtosis for the variable of interest during the pandemic. We also highlight that the Augmented Dickey-Fuller (ADF) test ensures stationarity of all VAR components.

The ARCH LM test points heteroscedasticity in the data. This should not hinder the present study, since the OLS estimation of the VAR coefficients upon which the underlying variance decomposition relies remain consistent under this circumstance, as discussed in Engle (1982).

In this stage we study the lead-lag relationship of the volatilities using a Granger causality test. For brevity, the results are reported only in a network plot, Fig.2, which is based on Zhang (2017). To perform this exercise, we used a VAR\(^7\) including all series simultaneously, then tested the null hypothesis that the coefficients of lagged index $i$ where jointly zero on equation for index $j$, for $i, j = 1, 2, ..., 11$. If the null hypothesis is rejected, index $i$ granger causes index $j$. The arrows in Fig.2 follow the direction of causality. Thus, in the pre-COVID-19 period the Energy sector causes all the other sectors except for Utilities, while the Consumer Discretionary sector is the most frequently granger caused. During the COVID-19 period Financials causes all the remaining sectors while Consumer Discretionary is again one of the most caused sectors.

4. Empirical results

4.1. Comparative static analysis

The price volatility connectedness tables of both pre-COVID-19 and COVID-19 periods are presented in Table 3. There are several points worth noting of which we highlight some.

First, total connectedness in the COVID-19 period, 84.5%, is much higher as compared to the pre-COVID-19 period, 65.9%. This increase is associated with a higher systemic risk during the pandemic as discussed in Diebold and Yilmaz (2014). There are many

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\(^5\) We have performed a data quality check, by comparing the used data with that available on the S&P global website. We have found only very few and small differences that are due to rounding.

\(^6\) For a background on the advantages of using absolute return as a measure of volatility, refer to Forsberg and Ghysels (2007). In the robustness section, however, we also analyze the effects of using conditional volatilities.

\(^7\) We selected the most adequate lag structure using the Akaike Information Criterion.
Fig. 1. Cumulative and daily percent returns of US sectoral indices.
Notes: The black line (left scale) represents cumulative returns. The grey bar plot (right scale) refers to the percent returns.
Table 2
Descriptive statistics based on sectoral price volatility (by denoted period).

| Panel A: Basic information - Pre-COVID-19 period (January 1, 2013–December 30, 2019) | SPLRC | SPLRCS | SPNY | SPSY | SPXHC | SPLRC | SPLRCT | SPLRCM | SPLRCREC | SPLRCL | SPLRCU |
|----------------------------------|--------|--------|-------|-------|-------|--------|--------|--------|--------|----------|--------|--------|
| Mean                             | 0.0067 | 0.0054 | 0.0091| 0.0074| 0.0067| 0.0067 | 0.0075 | 0.0075 | 0.0067 | 0.0073  | 0.0066 |
| Std                              | 0.0063 | 0.0049 | 0.0084| 0.0070| 0.0062| 0.0063 | 0.0075 | 0.0067 | 0.0061 | 0.0067  | 0.0057 |
| Skewness                         | 2.1764 | 1.7861 | 1.8013| 1.9567| 1.8139| 1.8511 | 2.0774 | 1.6634 | 1.8151 | 1.9870  | 1.7349 |
| Kurtosis                         | 10.5260| 7.7608 | 7.5038| 8.7920| 7.8241| 8.0486 | 9.1688 | 6.6086 | 7.8985 | 9.1113  | 7.9025 |
| Observations                     | 1.761  | 1.761  | 1.761 | 1.761 | 1.761 | 1.761  | 1.761  | 1.761  | 1.761  | 1.761   | 1.761  |
| Jarque-Bera                      | 5546.1***| 2599.3***| 2440.6***| 3585.2***| 2673.2***| 2875.9***| 4058.8***| 1767.5***| 2727.6***| 3899.1***| 2646.9***|
| Q(10)                            | 582.86***| 273.52***| 444.64***| 252.74***| 419.29***| 302.21***| 506.85***| 228.17***| 70.632***| 111.79***| 70.632***|
| ADF                              | -19.76***| -19.89***| -20.27***| -20.49***| -19.99***| -20.70***| -19.31***| -20.41***| -21.06***| -20.57***| -20.57***|
| ARCH LM                          | 42.404***| 58.028***| 43.747***| 55.374***| 40.167***| 35.468***| 73.238***| 70.875***| 74.098***| 14.375***| 11.791***|

| Panel B: Basic information - COVID-19 period (December 31, 2019–December 31, 2020) | SPLRC | SPLRCS | SPNY | SPSY | SPXHC | SPLRC | SPLRCT | SPLRCM | SPLRCREC | SPLRCL | SPLRCU |
|----------------------------------|--------|--------|-------|-------|-------|--------|--------|--------|--------|----------|--------|--------|
| Mean                             | 0.0139 | 0.0105 | 0.0254| 0.0187| 0.0122| 0.0161 | 0.0168 | 0.0162 | 0.0163 | 0.0135  | 0.0151 |
| Std                              | 0.0160 | 0.0142 | 0.0287| 0.0221| 0.0150| 0.0191 | 0.0194 | 0.0181 | 0.0200 | 0.0156  | 0.0193 |
| Skewness                         | 3.2077 | 3.1552 | 2.9818| 2.8606| 2.7185| 2.7549 | 3.0553 | 2.7623 | 3.5086 | 2.7334  | 3.0257 |
| Kurtosis                         | 18.0231| 14.8712| 15.8545| 13.4546| 12.1044| 12.7486| 15.9023| 11.9273| 22.2721| 13.2080  | 14.0519|
| Observations                     | 254    | 254    | 254   | 254   | 254   | 254    | 254    | 254    | 254    | 254     | 254    |
| Jarque-Bera                      | 2824.1***| 1912.9***| 2125.1***| 1503.1***| 1190.1***| 1327.0***| 2156.9***| 1401.0***| 4451.9***| 1419.0***| 1680.2***|
| Q(10)                            | 376.57***| 618.36***| 185.25***| 524.26***| 536.06***| 455.09***| 361.85***| 453.22***| 475.24***| 326.44***| 681.26***|
| ADF                              | -7.260***| -6.416***| -8.232***| -6.214***| -6.919***| -6.870***| -6.810***| -6.690***| -6.637***| -6.859***| -6.340***|
| ARCH LM                          | 11.120***| 91.340***| 0.3758 | 50.017***| 48.250***| 18.876***| 63.866***| 14.859***| 17.439***| 68.908***| 46.991***|

Notes: The above data represents daily sectoral price volatility for the period of January 2013 through December 2020. Data was obtained from Investing.com. *** denotes 1% level of significance. The Jarque-Bera test is used to check whether the price volatilities distribution is normal. The Box-Pierce-Ljung Q(10) statistic is distribute as a $\chi^2_{10}$ and test for autocorrelation. The augmented Dickey Fuller (ADF) is used to check the presence of unit roots. The ARCH LM test is used to investigate presence of heteroscedasticity, its null hypothesis is no ARCH effect.
candidates causes for the increase of sectoral connectedness during COVID-19, among usual factors expected in crises in general, as herd behavior, fire sales, policy action and feedbacks (Diebold and Yilmaz, 2015) as well as factors idiosyncratic of this pandemic, as the lockdown induced economic activity retraction or loss of job productivity discussed in Goodell (2020). From an asset pricing perspective, as discussed in Diebold and Yilmaz (2015) and Dungey et al. (2011), time varying connectedness could come from time variations of common factor loadings or of factor structure in a factor model.

Second, there are some radical changes in the connectedness of some indices. For instance, Utilities and Real State were the sectors that least received from the system in pre-COVID-19 period, with connectedness “from” of 41.3% and 56.9% respectively, while were the sectors that received the most from the system in COVID-19 period, 87.3% and 86.7%. Third, Industrials (Telecom) has been the sector with the highest (lowest) “net” connectedness with 18.6% (-19.1%) during pre-COVID-19 while during COVID-19 Industrials (Utilities) has been the sector with the highest (lowest) net connectedness, with 24.5% (-39.2%).

Fourth, Financials has increased its “net” connectedness by 7.5%, the highest jump among sectors with positive “net” connectedness on the pre-COVID-19 period. This result seems to corroborate Akhtaruzzaman et al. (2020) results that highlight the importance of financial sector to contagion transmission during COVID-19 pandemic in an international context. These last three points indicate that, in addition to a system wide change in the connectedness of the sectors, there have been considerable asymmetric changes across sectors and potentially in a pairwise manner.

To further investigate the changes in the directional pairwise net connectedness level, we use network representations in Fig.3, with all connections, and in Fig.4, only with the connections in the upper two deciles of magnitude, both in pre-COVID-19 and COVID-19 periods.

In both Fig.3 and Fig.4 the arrows go from the sector with positive net pairwise connectedness to its counterpart. Thus, for instance, Industrials sector possess positive net pairwise connectedness with all other sectors during the COVID-19 pandemic.

Fig.3 underline the fact that some considerable changes has been taking place during COVID-19 in the directional pairwise relations. In Fig.4 we can see that in the upper tail of pairwise connectedness the changes are even more pronounced during COVID-19. In fact, only 2 out of 12 of the connections that were among the most relevant before the COVID-19 remained in the top two deciles during the pandemic, namely Industrials-Energy and Discretionary-Real State. It is also apparent that there is a considerable concentration of strong pairwise connectedness to Utilities after COVID-19.

4.2. Dynamic analysis

4.2.1. Total connectedness rolling window plot

The previous section provided snapshots of both pre-COVID-19 and COVID-19 period, in a static form. It is arguable, though, that relationships are dynamically changing, mainly if one considers the possibility that the impact of COVID-19 over stock market has evolved considerably as it happened. To study the connectedness dynamics, we use rolling estimation windows of the connectedness indices.

We start by plotting the price volatility total connectedness over 100-day rolling-sample windows in Fig.5.

We first notice that there is considerable changing in the rolling windows estimation of total connectedness over time. The full
Table 3
Connectedness table based on sectoral price volatilities (by denoted period).

### Panel A: Connectedness table for pre-COVID-19 period (January 1, 2013 – December 30, 2019)

| S&P 500 Consumer Discretionary (SPLRCD) | SPLRCS | SPNY | SPSY | SPXHC | SPLRCI | SPLRCT | SPLRCM | SPLREC | SPLRCL | SPLRCU | FROM |
|-----------------------------------------|--------|------|------|-------|--------|--------|--------|--------|--------|--------|-------|
| 25.1                                    | 5.8    | 4.9  | 10.0 | 10.0  | 12.0   | 14.1   | 9.6    | 3.4    | 4.2    | 0.8    | 74.9  |
| 8.7                                     | 32.5   | 3.7  | 7.4  | 8.8   | 8.2    | 6.4    | 6.3    | 6.9    | 5.3    | 4.7    | 66.5  |
| 7.9                                     | 4.9    | 39.2 | 6.8  | 5.7   | 9.0    | 6.4    | 12.9   | 2.4    | 3.0    | 1.6    | 60.8  |
| 11.0                                    | 5.8    | 4.9  | 26.4 | 9.3   | 13.9   | 10.1   | 10.4   | 3.6    | 3.4    | 1.3    | 73.6  |
| 11.5                                    | 7.4    | 4.1  | 9.9  | 29.0  | 10.8   | 10.5   | 8.1    | 4.0    | 3.4    | 1.5    | 71.0  |
| 12.0                                    | 5.8    | 5.7  | 12.4 | 9.1   | 23.8   | 11.1   | 12.6   | 2.8    | 3.8    | 1.0    | 76.2  |
| 15.0                                    | 4.9    | 4.5  | 10.2 | 10.0  | 12.2   | 26.1   | 9.3    | 2.6    | 4.4    | 0.8    | 73.9  |
| 10.4                                    | 5.3    | 8.8  | 10.5 | 7.4   | 14.1   | 9.2    | 27.8   | 2.5    | 3.2    | 1.0    | 72.2  |
| 6.5                                     | 9.3    | 2.7  | 5.8  | 6.3   | 5.1    | 4.4    | 4.0    | 43.1   | 4.1    | 8.9    | 56.9  |
| 8.2                                     | 7.1    | 3.8  | 5.8  | 5.6   | 7.1    | 7.5    | 5.2    | 4.2    | 42.7   | 2.9    | 57.3  |
| 2.3                                     | 8.1    | 2.2  | 2.9  | 3.5   | 2.5    | 1.9    | 2.3    | 12.2   | 3.4    | 58.7   | 41.3  |
| **TO**                                  | 93.4   | 64.4 | 45.3 | 81.7  | 75.8   | 94.8   | 81.5   | 80.7   | 44.7   | 38.2   | 24.4  | 65.9  |
| **NET**                                 | 18.4   | -2.0 | -15.5| 8.1   | 4.7    | 18.6   | 7.6    | 8.4    | -12.3  | -19.1  | -16.9 |       |

### Panel B: Connectedness table for COVID-19 period (December 31, 2019 – December 31, 2020)

| S&P 500 Consumer Discretionary (SPLRCD) | SPLRCS | SPNY | SPSY | SPXHC | SPLRCI | SPLRCT | SPLRCM | SPLREC | SPLRCL | SPLRCU | FROM |
|-----------------------------------------|--------|------|------|-------|--------|--------|--------|--------|--------|--------|-------|
| 15.7                                    | 9.0    | 5.9  | 8.8  | 8.3   | 10.5   | 11.3   | 8.6    | 6.2    | 11.6   | 4.0    | 84.3  |
| 10.5                                    | 15.8   | 6.3  | 9.3  | 9.3   | 9.6    | 9.1    | 8.3    | 6.3    | 9.8    | 5.6    | 84.2  |
| 8.1                                     | 5.7    | 21.8 | 13.4 | 5.8   | 13.7   | 5.4    | 10.7   | 5.8    | 6.2    | 3.3    | 78.2  |
| 9.6                                     | 8.3    | 8.9  | 15.5 | 7.2   | 13.0   | 6.7    | 10.3   | 8.2    | 7.5    | 4.8    | 84.5  |
| 10.2                                    | 11.5   | 5.9  | 8.5  | 14.2  | 9.9    | 9.4    | 9.2    | 6.4    | 9.4    | 5.5    | 85.8  |
| 9.7                                     | 7.9    | 9.1  | 12.4 | 7.6   | 15.7   | 6.9    | 11.1   | 7.8    | 6.9    | 4.7    | 84.3  |
| 12.7                                    | 10.7   | 5.7  | 8.0  | 9.3   | 9.7    | 14.6   | 8.5    | 5.5    | 11.7   | 3.6    | 85.4  |
| 9.6                                     | 8.4    | 8.1  | 10.9 | 8.4   | 12.2   | 7.8    | 14.2   | 7.3    | 7.7    | 5.5    | 85.8  |
| 9.9                                     | 9.2    | 6.6  | 11.0 | 7.4   | 11.0   | 7.0    | 9.7    | 13.3   | 7.7    | 7.3    | 86.7  |
| 12.6                                    | 10.4   | 5.4  | 8.4  | 9.0   | 9.6    | 11.2   | 7.7    | 5.6    | 16.4   | 3.7    | 83.6  |
| 9.7                                     | 11.4   | 6.3  | 9.4  | 8.4   | 9.6    | 7.2    | 9.2    | 8.1    | 8.0    | 12.7   | 87.3  |
| **TO**                                  | 102.5  | 92.4 | 68.2 | 100.1 | 80.6   | 108.8  | 82.1   | 93.4   | 67.2   | 86.6   | 48.2  | 84.5  |
| **NET**                                 | 18.2   | 8.2  | -10.0| 15.6  | -5.2   | 24.5   | -3.3   | 7.7    | -19.6  | 3.0    | -39.2 |       |

Note: The predictive horizon is 12 days. The $ij$-th entry of the upper-left $11 \times 11$ sector index submatrix gives the $ij$-th pairwise directional connectedness, i.e., the percent of 12-day-ahead forecast error variance of firm $i$ due to shocks from firm $j$. The rightmost (FROM) column gives total directional connectedness (from), i.e., off diagonal row sums. The bottom (TO) row gives total directional connectedness (to), i.e., off diagonal column sums. The bottommost (NET) row gives the difference in total directional connectedness (to – from). The bottom-right element (in boldface) is the total connectedness.
sample extremes are 44.4% and 90.0%, against an unconditional mean of 65.9% before the pandemic and 84.5% during the COVID-19 period.

Observing the Fig. 5, one can see a reasonably stable period from the end of May 2014 to mid-August 2015, where connectedness oscillates in the range of 57.0% to 78.7%, followed by a significant increase of more than 20 points to 83.9% in the end of August 2015. This first considerable spike can be associated with turbulences in the US market due to spillovers of the China stock market crash occurred on August 24, 2015. The increased connectedness here observed indicates contagion from China to various sectors of US economy, likely with both economic and financial roots, as failing supply chain, depressed demand, as forced fire sales of invested assets and increased credit delinquency.

Beginning in mid-January 2016, there is a quasi-monotonic decay to the sample minimum, 44.4%, on January 12, 2018 which is followed by a huge spike on connectedness to pre-COVID maximum of 85.3% on February 5, 2018. On this day DJI plunged 1,175
points (4.60%), the biggest drop in points up to that moment during a single day, amid concerns with inflation and potential rising of interest rates. Put differently, this spike in connectedness coincides with fears of a tightening on monetary policy with impact over the of long-term interest rates, similarly to findings of Diebold and Yilmaz (2014).

After this point to the beginning of COVID-19 period, there has been alternating tranquil and turbulent moments, associated, for instance, with China-US trade tensions. Economically, the unstable connectedness of this period is in accordance with the view that bilateral trade linkage is a relevant factor for financial spillovers, as expressed in Ito and Hashimoto (2005).

Examining the COVID-19 period, the first noticeable feature of connectedness is the entire sample maximum of 90.0%, reached on February 27, 2020. On this day DJI has dropped 1,190 points (4.42%) after negative returns in the five previous trading sections, reaching a cumulative drop of 3,581 points (12.3%) since February 19, 2020 close. This early pandemic turmoil happened amid fears caused by a surge in COVID-19 cases outside China and the US report of the first case with no known travel link in northern California, on February 26, 2020. From this point on up to the end of July 2020 (day 23), the total connectedness was sustained in levels only seen during the COVID-19 period, including the acute crash of February 2018.

From august to the end of the sample we observe a gradual reduction in the connectedness levels, what is simultaneous to markets improvements driven, among other factors, by FED actuation, Government stimulus efforts, vaccines good news and subsequent FDA emergency approvals. At this point, it is fair to say that many uncertainties related to this pandemic have been resolved, with consequent improvements of markets and decrease of connectedness. However, it is unfortunately too soon to completely grasp how the pandemic will evolve from this point. Thus, it is probably premature to speculate on near future developments on sectoral connectedness as well.

Regarding potential economic implications of unprecedented connectedness found, one possible mechanism could be through failing credit supply. This is because this increase may have a role to play in the instability of financial market institutions. Nevertheless, we understand these implications have largely been mitigated by liquidity injections made by the central banks and governments worldwide. Put it another way, as COVID-19 is first of all an economic and secondly a financial crisis (Bouri et al., 2021), the fast acting of authorities following GFC experience have been providential to attenuate a possible feedback from financial system. Overall, we feel our findings have been more of a consequence than cause of further economic turmoil.

4.2.2. Directional connectedness rolling window plots
In this section we analyze the dynamic behavior of total directional -“to”, “from” and “net” - connectedness for all US sectoral indices. The underlying plots are presented in the three panels of Fig. 6.

We first evidence the fact that directional “from” connectedness is much smoother across sectors when compared to the “to” connectedness, what is in accordance with what is reported in Diebold and Yilmaz (2014), while analyzing the connectedness of 13 US financial institutions during the GFC. This fact is due primarily to asymmetric size and centrality of the sectors in US economy, which makes the spillovers of shocks to different sectors to have a wide range of responses.

Second, we observe that the “from” connectedness of all sectors finds its maximum during the COVID-19 period, in a pattern similar to that discussed in the previous section for the total connectedness index. On the other hand, the “to” connectedness reached the maximum during COVID-19 period for 6 out of the 11 indices studied, although there is a clear spike for all the indices surrounding February 27, 2020. We understand these findings indicate that COVID-19 had a homogeneous and unprecedented effect across sectors with regard to openness to other sectors spillovers while had a generally strong but asymmetric effect across sectors in regard to sending spillovers.

Considering the asymmetric nature of contribution from each sector to others, it is worth to highlight that the Energy sector have

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Fig. 5. Rolling total connectedness of price volatility.

Note: The rolling estimation window width is 100 days, and the predictive horizon for the underlying variance decomposition is 12 days.

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8 The Consumer Discretionary, Energy, Financials, Industrials, IT and Telecom Services sectors have reached its highest “to” connectedness during COVID-19.
(caption on next page)
shown the highest maximum values of “to” connectedness, 223%\(^9\), despite presenting modest average contributions both before (45.3%) and during the COVID-19 period (68.2%). This fact may be related to the findings of Zhang (2017) that show that oil prices are generally net receivers from stock markets but can contribute significantly when large shocks occur. Financials shows the second highest maximum, 195%, what is in accordance with the common view that this is a sensible sector in crisis scenarios.

Third, turning now to the “net” connectedness, we highlight that most sectors maintained their status as predominantly net receivers/senders of connectedness during COVID-19 as compared to pre-COVID-19 period, the only two exceptions were IT and Health Care both of which were predominantly net senders (receivers) before (during) the pandemic. For instance, the Energy sector had positive “net” connectedness during 23.0% (35.6%) of the time before (during) the pandemic making it a predominantly net receiver of connectedness from the system in both periods. Once more we highlight the Financial sector, that was a net sender of connectedness in 67.8% (88.9%) of the time before (during) the COVID-19 period, having experienced the highest growth in that proportion among all sectors.

5. Robustness check

To examine sensitivity to parameters definition, we compute the rolling total connectedness index using the baseline parameters - window width (W) of 100 days, predictive horizon for the underlying variance decomposition (H) of 12 days and VAR lag structure (p) of 3 – and close values. The results are in Fig. 7. There we can see that most of the time the 25%-75% quantiles range of the obtained distributions is very narrow and contains the baseline value and that even the extremes maintain a generally close relation to baseline computation.

We also examine the effects of using an alternative definition of volatility over the measure of total connectedness. The results are in Fig. 8. Following Antonakakis et al. (2018), we use conditional volatilities. We obtained the conditional volatilities extracted from best fit univariate volatility models\(^{10}\). Fig.8 is remarkably similar to Fig. 7. Particularly, all the features discussed in the Section 4.2 remain present.

Finally, to check if the results were driven by outliers, we used the moving average of the returns volatilities as the variables of interest and recomputed the total connectedness index. In this configuration, the features discussed on Section 4.2 once more hold. For brevity, the related plots are not reported and will be provided from authors upon request.

6. Conclusions

The COVID-19 pandemic provides a unique backdrop to re-examine connectedness between economic sectors during crises, even more so if one considers the concomitant Russia-Saudi Arabia oil price war. Adding to the literature on financial markets effects of COVID-19, employing the connectedness indices of Diebold and Yilmaz (2009, 2012, 2014), we develop comparative static and dynamic analysis of the price volatility connectedness of US sectoral indices aiming to unveil quantitative and - possibly - qualitative changes and stylized facts occurred during an exceptional crisis period. The pre-COVID-19 is chosen to be January 01, 2013 to 30 December 2019, a relatively stable period not overlapping the last major economic crisis. The COVID-19 period is from December 31, 2019 to December 31, 2020.

Among several results, we find there has been extraordinary increase in connectedness among US sectoral indices volatility during COVID-19, lasting from earlier stages of international spread of cases in the end of February to the end of July, 2020. This increase aligns with the observed behavior in previous crises as reported in Barunik et al (2016) and Mensi et al. (2020), for instance; unprecedented and homogeneous increase in how much volatility spillovers each one of the indices receives from the system; a considerable but asymmetric increase in how much spillovers each index sends to the system; qualitatively, considerable changes in pairwise relationships, especially among the connectedness links in the upper two deciles of magnitude, however, in a total net connectedness perspective, there is little evidence of structural changes in relationships - in the sense that most indices have maintained their status as net senders/receivers of connectedness to the system during the pandemic as compared to the previous tranquil period; the Energy sector reached the highest daily value of connectedness “to” the system, even being an average net receiver of connectedness both before and during the pandemic in accordance with Zhang (2017) perceptions; the Financials sector has shown to be relevant sender of connectedness during the pandemic in several metrics.

Regarding practical use, our findings seem to indicate a unprecedented increase in the network connectedness of US sectors during a severe crisis moment. The implication would be that little sectoral diversification advantage could eventually be expected in such harsh moments. Risk managers gain in verify how extreme sectoral connectedness can be in practice, and consequently adjusting stress

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9 As the “to” connectedness are sums of errors variances shares in forecasting 10 sectors due to the remaining sector, its value is not limited to 100%.

10 Considering the characteristics of financial data, we searched for each index the best model among ARCH, GARCH, A-GARCH, TARCH and A-TARCH alternatives using the Akaike Information Criterion as a selector.
tests scenarios. Asset pricing models could benefit of considering sectoral factors during turbulent moments.

For the policy makers, first, the results indicate relevance of specific sectors during turbulent periods, in particular, the sectors that send spillovers more intensely and those that are the most prone to receiving them. This identification could be used to target supporting and possibly macroprudential type policies. Second, as the increase of connectedness seems to indicate crisis intensity, the dynamic analysis could serve as real-time crisis monitoring instrument, as suggested in Diebold and Yilmaz (2015).

Submission declaration

With the submission of this manuscript, we would like to undertake that it has not been published elsewhere, accepted for publication elsewhere or under editorial review for publication elsewhere; The publication is approved by all authors and that our institutions representatives are fully aware of this submission. Also, if accepted, it will not be published elsewhere in the same form, in English or in any other language, including electronically without the written consent of the copyright-holder.

CRediT authorship contribution statement

Antonio Costa: Conceptualization, Validation, Formal analysis, Investigation, Writing - original draft, Writing - review & editing, Methodology, Software, Visualization. Paulo Matos: Supervision, Conceptualization, Writing - original draft, Writing - review & editing. Cristiano da Silva: Supervision, Conceptualization, Writing - review & editing.
Declaration of Competing Interest

None.

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