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How Do US Sectoral Markets Connect in Calm and Crisis? A Quantile-Based Network Analysis

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Abstract

This work investigates how the returns coherence of the US sectoral market changed during/post COVID-19 from the pre-pandemic period. We sampled daily data for a pre-COVID-19 period from January 2018 to November 2019 and a during/post-COVID-19 period from December 2019 to August 2024. To compare the returns coherence and spillover for these periods, we applied quantile cross-spectral (Baruník & Kley, 2015) and network connectedness (Diebold & Yilmaz, 2014) measures, respectively. Our results highlighted a substantial increase in the integration level of US sectoral returns during/post-COVID-19 period. The effects of COVID-19 on returns were found to be more prominent with a short-run investment horizon under extreme market conditions. However, the coherence of energy sector returns with all other sectors remained low during/post-COVID-19 period under normal and bullish market conditions, thereby offering optimal opportunities for investment.

Keywords: *COVID19; US sectoral returns; quantile cross spectral; network connectedness.*

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Abstract

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Keywords: *COVID-19; US sectoral returns; network connectedness; quantile cross-spectral.*

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1. Introduction

Once the World Health Organization (WHO) announced a worldwide emergency[1] owing to the COVID-19 pandemic,[2] it led to severe shifts in the global economy (McKibbin & Fernando, 2020; Şenol & Zeren, 2020), where economic uncertainty increased (Baker et al., 2020a), economic policies modified (Caballero & Simsek, 2020; Huang et al., 2020a), and poverty increased (Sumner et al., 2020). Moreover, unemployment became greater (Ludvigson et al., 2020), and risk and volatility in financial markets (Garcin et al., 2020; Okorie & Lin, 2020), as well as a rise in alternative investments (Nautiyal et al. 2024; Abdelrhim et al., 2020). However, the COVID-19 pandemic not only caused severe disruption to economic activity but also acted as a driver of risk and volatility in financial markets. Rizwan et al. (2020) reported that banking risk significantly increased in the world's eight major economies, namely France, Canada, China, Spain, Germany, Italy, UK and USA. Likewise, Albulescu (2020) revealed the significant influence of the pandemic (COVID-19) on the volatility of financial markets. Kang et al. (2023) also found there was a significant growth in the volatility of the stock market in the USA during the period of COVID-19. The behavior of stock markets is not simple or linear in nature, with empirical studies reporting the sensitivity of financial markets to major events like natural disasters (Worthington, 2008; Wang & Kutan, 2013), political uncertainty (Apergis et al. 2023), geopolitical risks (Hoque & Zaidi, 2020),

[1]See the reports published by WHO, www.who.int/emergencies/diseases/novel-coronavirus-2019/situation-reports.
[2] The coronavirus disease (COVID-19) arose in 2019 in China, Wuhan City. On January 7, 2020, Chinese officials reported it as a new type of coronavirus. This very virus put the entire world at enormous risk and caused fear and in March 11, 2020 WHO announced that the COVID-19 had caused a pandemic.

news announcements (Knif et al., 2008; Hussain & Omrane, 2020), and pandemics (Ichev & Marinč, 2018). Nonetheless, the unprecedented impact of the COVID-19 pandemic on stock markets, as has been recently documented, was far greater in magnitude. For instance, Baker et al. (2020b) argued that the effect of COVID-19 on stock markets was greater than any previously recorded pandemic, including the 1918 Spanish flu. Shehzad et al. (2020), meanwhile, argued that COVID-19 had a substantial influence on the German, Italian, and American stock markets greater than the financial crisis of 2008. Similarly, Chowdhury and Abedin (2020) reported the significant influence of the pandemic (COVID-19) on US stock market returns. On a similar note, Azimli (2020) found that the COVID-19 pandemic substantially influenced US sectoral returns. Thus, based on the evidence of contagion caused by different crisis periods, we employed the quantile coherency measure introduced by Baruník and Kley (2015), because this would be important for quantifying any general dependence structure in different quantiles of a joint distribution. We also measured the network connectedness using the measure proposed by Diebold and Yilmaz (2014), which has advantages over alternative approaches because it gives information about the magnitude and direction of the return transmission.[3] Additionally, it enabled us to identify instances of abrupt, temporary increases in return transmission.

Our work addresses key gaps in the existing strand of studies on the connectedness of sectoral return. First, it, identifies significant changes in the returns connectedness among US sectors during and after the COVID-19 outbreak, comparing correlations between two distinct periods: pre-pandemic and during/post-pandemic. Most prior studies (e.g. Ramelli & Wagner 2020; Lee 2020; Ngwakwe 2020; Rehman et al. 2023) have focused on aggregate markets and the immediate pandemic effect. In contrast, we provide a sector-specific analysis of the US economy, recognizing its dominant role

[3] From variable A to variable B, from variable B to variable A, or both.

in global finance and its significant share of global investor's interest[4]. We add fresh evidence, extending the timeframe to August 2024, thereby capturing both the short- and long-term contagion across sectoral equities. Second, unlike studies that examine return connectedness during average market conditions, our analysis is based on comparing return connectedness across normal and extreme market conditions. Using quantile cross-spectral analysis, we construct a network-based visualization to illustrate how risk transmission evolved across sectors during and after pandemic conditions, underlining detailed inter-sectoral relationships and contagion effects that studies on aggregate markets may overlook. According to Alomari et al. (2022) and Narayan et al (2023), ignoring these cross-sector differences can compromise portfolio diversification, as assuming uniform pandemic impacts across sectors may lead to significant losses. In this spirit, the varied sectoral effects during/after the COVID-19 period emphasize the need for sector-specific analysis to strengthen portfolio resilience and risk management, providing valuable lessons for future pandemic-induced turmoil. Another contribution of our work is the application of quantile cross-spectral, which, unlike the quantile-VAR-based (QVAR) method, focuses on directional spillovers in the time domain. It, therefore, provides a subtle analysis by operating cyclical and periodic dependencies in the frequency domain (Barunik & Kley, 2019), revealing relationships not apparent in the time domain.

Our results highlight a significant increase in correlation among US sectoral returns during/post-COVID-19 pandemic. We found that US sectoral returns were more influenced by the COVID-19 pandemic during a short-run investment period under extreme market conditions. Among all the

[4] US market accounted for over 38% of global stock trades and 40% of market capitalization relative to GDP (World bank report, 2019). https://data.worldbank.org/indicator/CM.MKT.TRAD.CD/

sectors, the energy sector provided the best cover against COVID-19 by having a low coherence under medium- and long-run periods.

The rest of our paper is presented as follows: Section 2 explains the applied methodologies in detail while Section 3 gives information about the data and analysis for quantile cross-spectral and network connectedness methods. Finally, Section 4 concludes this work by discussing the implications for investors.

2. Data and Methodology

i) Data

Our empirical exercise employs the S&P 500 composite index and ten U.S. equity sectors datasets: consumer discretionary, consumer services, energy, financials, healthcare, industrials, materials, real estate, technology and utilities. The dataset spans from 1st January 2018 to 16th August 2024, covering the pre- and post-COVID-19 periods. The full sample is divided into two sub-periods: the pre-pandemic period (January 1, 2018, to 29th November 2019) and the pandemic and recovery period (December 2, 2019, to August 16, 2024). This timeframe allows us to capture both the market's immediate reaction to the pandemic and its longer-term recovery. The starting point of December 1, 2019, is selected as the beginning of the COVID-19 crisis, aligning with the first reported case in China (Huang et al., 2020b). All data were sourced from Eikon Thomson Reuters DataStream.

ii) Quantile cross-spectral method

The quantile coherency measure introduced by Baruník and Kley (2015) was employed to quantify the dynamic dependence (DD) of both the (X_{tj1}) and (X_{tj2}) processes as:

$$\Re^{j_1,j_2}(\omega;\tau_1,\tau_2) = \frac{f^{j_1,j_2}(\omega;\tau_1,\tau_2)}{(f^{j_1,j_1}(\omega;\tau_1,\tau_1)f^{j_2,j_2}(\omega;\tau_2,\tau_2))^{1/2}} \quad (1)$$

where $f^{j_1 j_2}$, $f^{j_1 j_1}$, and $f^{j_2 j_2}$ denote the quantile cross-spectral, in addition to the quantile spectral densities of processes (X_{tj1}) and (X_{tj2}), for every $j \in \{1,...,d\}$ and $\tau \in [0,1]$, respectively, and they were derived from the Fourier transform of the "matrix of quantile cross-covariance kernels" (MQCCK):

$$\Gamma_k(\tau_1\tau_2) := \left(\gamma_k^{j_1,j_2}(\tau_1\tau_2)\right)_{j_1 j_2=1,\ldots,d'} \tag{2}$$

where

$$\gamma_k^{j_1,j_2}(\tau_1\tau_2) := \mathrm{Cov}\left(I\{X_{t+k,j_1} \le q_{j_1}(\tau_1)\}, I\{X_{t,j_2} \le q_{j_2}(\tau_2)\}\right) \tag{3}$$

For event A, $j \in \{1,...,d\}$, $k \in Z$, $\tau_1, \tau_2 \in [0,1]$, and the indicator function is $I\{A\}$. This model corresponds to the difference in copula $\left(X_{t+k,j_1}, X_{t,j_2}\right)$ and the independence copula. According to Baruník and Kley (2015), significant information about serial dependence and cross-sectional dependence can be taken by allowing k to vary and taking $j_1 \neq j_2$. Regarding the frequency, this generates the "matrix of quantile cross-spectral density kernels" (MQCSDK), as shown in the below equation

$$\mathbf{f}(\omega; \tau_1,\tau_2) := \left(f^{j_1 j_2}(\omega; \tau_1,\tau_2)\right)_{j_1,j_2=1,\ldots,d} \tag{4}$$

where

$$f^{j_1 j_2}(\omega; \tau_1,\tau_2) := (2\pi)^{-1} \textstyle\sum_{k=-\infty}^{\infty} \gamma_k^{j_1,j_2}(\tau_1\tau_2) e^{-ik\omega} \tag{5}$$

The "quantile coherency matrices" (QCM) for three quantiles (i.e. 5%, 50% and 95%), with all their mixtures, were then obtained. Furthermore, these frequencies were classified as long-term (250 days), medium-term (22 days), and short-term (2 days).

Our selection of quantile cross-spectral is due to its advantages in capturing time-varying, frequency-based relationships across quantiles. Unlike the quantile-VAR-based (QVAR) method, which focuses on directional spillover in the time domain, the quantile cross-spectral approach provides a subtle analysis by operating cyclical and periodic dependencies in the frequency domain (Barunik & Kley, 2019), revealing relationships not apparent in the time domain. This method excels in measuring dependencies among extremes, making it well-suited for financial applications where tail behavior is critical. While QVAR captures nonlinear relationships and enables impulse response analysis, the quantile cross-spectral method offers superior insights into frequency-dependent relationships and tail dependencies, making it highly suited to our study data. We also integrate Diebold and Yılmaz (2014) network connectedness approach as a robustness measure for examining the magnitude and direction of returns transmission between sectors. These combined methods explain evolving patterns of risk spillover, offering significant implications for different market stakeholders.

The concept of quantile coherency is based on the work of Baruník and Kley (2019), who introduced the quantile cross-spectral analysis framework. Our choice of quantiles is made to represent median behavior and tail dependencies. This approach is consistent with recent literature such as Baruník and Kley (2019) and Belhassine & Karamti (2021) which emphasizes the importance of examining tail dependencies and median characteristics.

The selection of time windows for short, medium, and long-term periods is grounded in established market practices and existing financial literature, including Belhassine & Karamti (2021) and Rehman et al. (2022a). These studies typically divide the investment horizon into short-term (2 days) and long-term periods extending to 256 days or more. Specifically, the 250-day period aligns with a standard trading year, commonly used to identify long-term market trends. The 22-day window represents approximately one trading month, which is a conventional medium-term measure for capturing short-term market dynamics. The 2-day window is designed to capture very short-term movements, aligning with microstructure noise in high-frequency trading data, a widely accepted tool in technical analysis (Baumöhl & Shahzad, 2019).

ii) Return connectedness

To quantify the return connectedness among US sectoral returns, we used a connectedness measure built from pieces of the variance decomposition method suggested by Diebold and Yilmaz (2014). Now, the ij^{th} H-step variance decomposition component is denoted as d_{ij}^{H}. The measures of connectedness are subsequently built on non-own or cross-variance putrefactions, such that d_{ij}^{H}, $i,j = 1,\ldots,N$, $i \neq j$.

Then, an N-dimensional covariance stationary data-generating process with orthogonal shock was taken into account as follows: $x_t = \Theta(L)u_t$, $\Theta(L) = \Theta_0 + \Theta_1 L + \Theta_2 L^2 + \ldots$, $E(u_t, u_t') = I$, where Θ_0 needs to not be diagonal. The contemporaneous features of connectedness are summarized in Θ_0, whereas the dynamic features lie in $\{\Theta_1, \Theta_2 \ldots\}$. In order to summarize the connectedness, we need to transform $\{\Theta_1, \Theta_2 \ldots\}$ via the variance decomposition.

----INSERT TABLE 1----

Table 1 presents the measure suggested by Diebold and Yilmaz (2014) in an attempt to help understand underlying connectedness. The upper left NxN block in the connectedness table comprises the variance decomposition matrix symbolized as $D^H = [d_{ij}]$. The table of connectedness upsurges D^H, with the rightmost column representing row summations and the element at the bottom right representing grand averages, in all cases for $i \neq j$. Gross pairwise directional connectedness (GPDC) going from variable j to variable i may be expressed as follows in equation 6.

$$C_{i \leftarrow j}^{H} = d_{ij}^{H} \tag{6}$$

where $C_{i\leftarrow j}^{H} \neq C_{j\leftarrow i}^{H}$. We estimate the net pairwise directional connectedness (PDC) going from the j variable to i variable as presented in equation 7 below:

$$C_{ij}^{H} = C_{j\leftarrow i}^{H} - C_{i\leftarrow j}^{H} \tag{7}$$

The off-diagonal column summations in Table 1 show the share of the H-step forecast error variance of variable x_i giving rise to shocks in other factors, whereas the off-diagonal row summations represent the share of H-step forecast error variance of factor x_i in response to shocks in other variables. The off-diagonal column and row summations in the connectedness table are therefore labeled as "to" and "from," thereby suggesting the total connectedness measures. Specifically, total directional connectedness from all other variables to variable i can be expressed as $C_{i\leftarrow \bullet}^{H} = \sum_{\substack{j=1 \\ j\neq i}}^{N} d_{ij}^{H}$, while the total directional connectedness from variable i to all other variables can be expressed as $C_{\bullet\leftarrow i}^{H} = \sum_{\substack{j=1 \\ j\neq i}}^{N} d_{ij}^{H}$. Hence, the net directional connectedness can be calculated as

$$C_{i}^{H} = C_{\bullet\leftarrow i}^{H} - C_{i\leftarrow \bullet}^{H} \tag{8}$$

The grand total of the off-diagonal entries in D^{H} then measures total connectedness as:

$$C^{H} = \frac{1}{N}\sum_{\substack{i,j=1 \\ j\neq i}}^{N} d_{ij}^{H} \tag{9}$$

The variance decompositions are estimated differently from the non-orthogonal since the variance of a weighted sum is not considered a suitable sum of variances, so in all cases, providing orthogonal innovations similar to the typical Cholesky-factor identification might be sensitively affected by ordering. Therefore, we used the generalized VAR decomposition, as proposed by Diebold and Yilmaz (2014), having been introduced by Koop et al. (1996) and Pesaran and Shin (1998), because this is invariant to collation. The H-step "generalized variance decomposition matrix (GVDM)" was then computed as $D^{gH} = \left[d_{ij}^{gH}\right]$ as follows:

$$d_{ij}^{gH} = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left(e_i' \Theta_h \Sigma \, e_j\right)^2}{\sum_{h=0}^{H-1} \left(e_i' \Theta_h \Sigma \, \Theta_h' e_j\right)} \tag{10}$$

where $\Theta_h$is the coefficient matrix, e_j is the vector jth element unity and zero elsewhere, σ_{jj} is the jth diagonal element, and $\sum$ is the covariance matrix of the shock vector in the non-orthogonalized VAR. The lack of orthogonality in the generalized variance decomposition framework implies that the rows of d_{ij}^{gH}do not have to sum up to unity. In order to obtain the generalized connectedness index $\tilde{D}^g = \left[\tilde{d}_{ij}^g\right]$, we need to normalize $\tilde{d}_{ij}^g = \frac{d_{ij}^g}{\sum_{j=1}^N d_{ij}^g}$ by computing $\sum_{j=1}^N \tilde{d}_{ij}^g = 1$ and $\sum_{i,j=1}^N \tilde{d}_{ij}^g = N$. The matrix $\tilde{D}^g = \left[\tilde{d}_{ij}^g\right]$ then allows us to measure the total connectedness, total directional, and net total directional.

3. Analysis and discussion

Some descriptive statistics for our sampled US sectoral returns are reported in Table 2. The highest average daily returns were seen in the consumer discretionary sector (0.04 percent), while the greatest losses of around 0.09 percent were incurred by the energy sector. Among all the sectors, only the energy and financial sectors experienced an average loss, suggesting suboptimal performance for these sectors. Over the sampling period, the highest levels of daily returns and losses were seen for the energy sector (15.11% and 22.42%, respectively), reflecting the volatile nature of this sector. According to the standard deviation of returns, the greatest volatility was indeed exhibited by the energy sector (approximately 2.38%). These results propose that the energy sector is one of the most active in the US equity market with the lowest daily returns, greatest volatility for returns, and both the highest and lowest individual daily returns over the sampling period. The skewness and kurtosis values imply that the returns distributions for all the sectors is negatively skewed with a fat tail (i.e., a lepto kurtic distribution). These findings are further supported by the Jarque Bera statistics, which suggest that the returns for all the sectors are not distributed normally. To examine the presence of a unit root in our return series, we utilized the Augmented Dickey-Fuller (ADF) and Phillips–Perron (PP) tests, whereas the assumption of stationary in the series was tested using the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test. We give the results, up to the 20th order, of both squared residuals and serial correlation in the residuals. The findings of the Ljung–Box test highlight the presence of a temporal dependence in the residuals of the model. We also utilized the Lagrange multiplier test to investigate for conditional heteroscedasticity up to the 20th lag order, which would in turn indicate the presence of an ARCH effect.

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Figure 1 illustrates the pricing trends for the US sectors before and during/post-COVID-19. From 2018, we see stable prices for all sectors until the end of 2019, when the emerging COVID-19 phenomenon started affecting financial markets all around the globe. The COVID-19 pandemic also affected the US equity market to a great extent, which was clearly evidenced by a sharp decline in prices across all the sampled sectors. These results support the findings of Chowdhury and Abedin (2020), who reported that US stock market returns significantly decreased due to COVID-19. The period from February to March 2020 most affected all the sectors, with the pricing indexes declining substantially. From April 2020 onwards, most sectors experienced a recovery, but the pace was different. Real estate, energy, and utilities were slower to regain pre-COVID levels. In 2022, the Ukraine war triggered another drawdown, causing global supply chain disruptions and spiking energy costs, leading to declines across several sectors, particularly consumer materials, communications, consumer discretionary, technology, and industrials. However, since 2023, most sectors began to recover, but consumer discretionary and real estate lagged, not reaching their pre-

Ukraine peak by August 2024. The S&P 500 index demonstrated a robust recovery following the pandemic, achieving record highs in 2022 and August 2024. However, during this period, the index faced a notable decline in early 2022 due to the geopolitical uncertainty and economic disruptions caused by the Ukraine conflict, which led to increased volatility and market corrections.

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Figure 2 presents a comparison of unconditional correlation before and during/post-COVID-19 period. This side-by-side comparison of the two sample periods suggests that the returns correlation significantly increased after the onset of COVID-19. Our results agree with those of Zhang et al. (2020), who found that US stock returns were highly correlated at the start of the COVID-19 pandemic. This increase in correlation was not incremental but instead ranged between two and three times greater in magnitude for most cases when compared to the pre-pandemic period. For example, among many other cases, the correlation of healthcare with the real estate and utilities sectors increased from 0.49 to 0.87 and 0.32 to 0.65, respectively. Such cases can be observed across most sectors, suggesting that not just US sectoral returns were significantly affected by COVID-19, but also that returns integration and transmission sharply increased following the contagion. These results are in line with the findings of Okorie and Lin (2020) and Rehman et al. (2022b) who suggested that COVID-19 had a fractal contagion influence on US, Chinese and European sector stock markets respectively, that changed over time for both stock market volatility and returns.

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Figure 3 illustrates the results for conditional volatility as modeled by the GARCH process. We can see how the stable pattern of returns for the US sectors before COVID-19 transformed into an abnormally volatile pattern in early 2020. This supports the findings of Mazur et al. (2020) and Choi (2020) who found that the volatility of some US sectors (real estate, entertainment, hospitality, and petroleum) increased substantially in response to COVID-19. This volatility in returns remained high until March 2020, when most of the markets started regaining some balance. Although the volatilities of all the US sectors declined after March 2020, they remained high relative to the pre-pandemic period. Our findings are in line with those of Baker et al. (2020c), Shehzad et al. (2020); Zhang and Hamori (2021) who documented that the volatility of US stocks in mid-March 2020 exceeded that reported in both October 1987 and December 2008. However, this volatility started to retreat by late March 2020, with it dropping sharply but lingering well above the pre-pandemic level.

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Figure 4 shows the findings of the quantile cross-spectral analysis, which indicates the presence of returns coherence among different sectoral returns in the USA under various investment horizons and market conditions. For the sake of brevity, we present a comparison of pre-COVID-19 and during/post-COVID-19 returns coherence under short-, medium-, and long-run investment periods and bearish, normal, and bullish market circumstances. A more detailed depiction of returns coherence under a wide array of quantile arrangements is presented in the appendix. Figures 4a and 4b present the returns coherence results under a short-run investment period, and we can see a substantial difference in sectoral returns coherence before and during/post-COVID-19 period (Öztürk et al., 2020). The pre-COVID-19 results highlight numerous diversification opportunities due to the low returns coherence. For example, the real estate and utilities sectors offered the best diversification opportunities compared to the other sectors. A few cases—such as the healthcare, materials, services, discretionary, financial, and IT sectors—exhibited high coherence values among themselves before the COVID-19 pandemic, and these increased further during/post COVID-19 period. These results concur with those of Liew and Puah (2020), who found that COVID-19 had a negative influence on the returns of the Chinese healthcare, materials, discretionary, financial, and IT sectors. We also observe interesting results under normal market conditions for the short-run investment horizon, as the high returns coherence values before COVID-19 dropped during/after the pandemic. This suggests that COVID-19 affected extreme market returns, which would be in line with the results of Azimli (2020), who found that the degree of dependence among returns and market portfolios increased only under higher quantiles during/post COVID-19 pandemic. Another interesting observation is the changing pre-COVID-19 coherence level of the materials sector in relation to services, discretionary, financial, and IT sectors, as well as the consumer discretionary sector with the real estate, industrial, energy, and utilities sectors which become low during/after the COVID-19 period. Under bullish market conditions in the short run, the results resemble those under bearish conditions, with a strong increase in returns coherence during/after the COVID-19 period. This is supported by Akhtaruzzaman et al. (2020), who found that firms experienced significantly higher return correlations during/after the COVID-19 period. The real estate, industrial, energy, and utilities offer diversification opportunities with most other sectors, however, during/after the COVID-19 period, these opportunities disappeared. For example, among other sectors, negative correlation values for the utility sector with the industrial and energy sectors changed to 0.5 in both cases. These findings are comparable with Vo and Hung (2021) and Shahzad et al. (2021) who evidenced a higher level of return connectedness across various asset classes during the COVID-19 period compared to pre-COVID-19, leading to reduced diversification gains. Further, Rizvi et al. (2020) also identified sector-specific reactions to the COVID-19 pandemic, consistent with our observations.

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Figures 5a and 5b present the quantile coherence results for the medium-run period. In bearish and normal market conditions, the level of returns coherence among US sectoral returns nominally increased from the pre-COVID-19 period to the during/after a period of COVID-19. However, the real estate and utilities sectors, both under bearish and normal market conditions, saw diminished diversification opportunities with other sectors following the onset of COVID-19. These findings support those of Rehman et al. (2020a), who found that the volatility of international real estate equities increased during/after COVID-19. Similarly, Liew and Puah (2020) reported a significant decline in returns within the utility sector during/post-COVID-19 period. Another noticeable change is observable for the energy sector, because its returns coherence with all other sectors decreased significantly during the pandemic, thereby presenting opportunities for optimal investment. Under bearish market conditions, the returns coherence increased sharply among almost all sectors for the medium-run investment horizon, with the energy sector being the only one where the returns coherence decreased substantially. This highlights the potential of the energy sector to provide cover under extreme market conditions with a medium-run investment horizon. This finding corroborates previous research on commodity-equity linkages, such as Kilian & Park (2009) and Arouri et al. (2011), who highlighted the energy sector's defensive nature and the return spillover between oil and equity markets. Szczygielski et al. (2021) maintain that COVID-19 uncertainty negatively affects the risk-return profiles of energy sectors. In the same spirit, Salisu et al. (2019) report that energy sector firms can hedge against market fluctuations. Ashraf (2020), and Matos et al. (2021) also concluded that a negative correlation between energy stock returns and the pandemic across multiple countries. However, Hernandez et al. (2022) recorded opposite findings, indicating the highest connectedness for the energy sector during COVID-19 in the US.

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Figures 6a and 6b present the quantile coherence results for the long-run investment period, and they highlight how under each market condition (i.e., normal, bearish, and bullish), the coherence level increased during/after the period of COVID-19, particularly during bullish state. These outcomes support the findings of Mazur et al. (2020), who reported that the US natural gas, food distribution, healthcare, software, and technology sectors performed significantly during/after the COVID-19. Interestingly, the real estate sector provided cover for the discretionary, financial, IT, and industrial sectors under normal market conditions, whereas the energy sector provided weak coherence during/after the COVID-19 period. Overall, our findings suggest that the energy sector offered opportunities for diversification throughout COVID-19 for medium- and long-run investment periods under bullish market conditions. This indicates that while diversification opportunities existed, the pandemic's influence on prices persisted, leading to leading to weaker coherence in the energy sector under normal and bearish conditions. This may be further supported by the notion that the effect of uncertainty on energy sector stocks extends beyond crisis periods. For instance, Sharif et al. (2024) maintain a similar conclusion of weak pandemic impact on energy return. Bianconi and Yoshino (2014) report that greater uncertainty negatively affects energy returns in 24 countries, while Fazelabdolabadi (2019) notes that uncertainty related to oil prices and economic policy decreases energy sector returns and increases volatility in Iran. Additionally, Zhu et al. (2020) highlight that investor sentiment during COVID-19 contributes to pricing anomalies in energy stocks.

----INSERT FIGURE 6a-6b----

Figures 7a to 7c illustrate the results for network connectedness. More specifically, Figure 7a plots the results for network connectedness over the complete sample period, highlighting how the communications sector was the major recipient of change from all other sectors, with the healthcare and financial sectors transmitting the most spillover. Similar results have also been documented by Baruník et al. (2016), who found that asymmetric return flows from the US healthcare and financial sectors to other sectors. Other sectors transmit significant spillovers toward the communication sector, including the technology, discretionary, materials, and real estate sectors. The energy, industrial, and utility sectors also actively transmit returns toward the communications sector, albeit at a lesser magnitude. Besides the communications sector, no sector propagates any change toward any other sector. The complete sampling results, however, include the COVID-19 period, when the world's financial markets, including the US sectoral market, behaved differently. Figure 7b shows the results for the pre-COVID-19 period, during which the financial, utility, and technology sectors played a dominant role in transmitting change toward other sectors. The utility sector transmitted change toward the real estate sector, while the technology and financial sectors—along with the industrials and discretionary sectors and the S&P500, albeit at a lower magnitude—transmitted change toward the communication sector. Among all the sectors, the materials sector was a major recipient of spillover, with all sectors other than real estate transmitting it. Figure 7c presents the network connectedness throughout the COVID-19 period, revealing how the communications sector was a major recipient of spillover from all other sectors at a high magnitude. However, no significant spillover was witnessed among the other sectors, although the real estate sector received nominal spillover from the financial, industrial, technology, and materials sectors. Overall, the COVID-19 period saw increased transmission of spillover, with it mainly being directed at the communications sector from all other sectors.

----INSERT FIGURE 7a-7c----

4. Conclusion

We compared US sectoral returns before and during/after the COVID-19 pandemic, focusing on healthcare, materials, services, discretionary, financial, technology, real estate, industrial, energy, and utilities sectors, alongside the S&P 500. Our pre-COVID-19 period spanned from 1st January

2018 to 1st December 2019, while during/after the COVID-19 period extended from December 2019 to 17th August 2024. We applied a quantile cross-spectral method to measure the structural dependence and connectedness among US sectoral returns across different market conditions and frequencies. Additionally, we used the network connectedness approach to assess spillovers among various sectoral returns. Our results revealed substantial differences in the level of integration of sectoral returns coherence before and during/after the COVID-19 pandemic. Investors should consider the effect of any crisis period when making investments in the US sectoral market. We found that the effect of the COVID-19 pandemic was more pronounced under extreme market conditions across quantiles. The healthcare, materials, service, discretionary, financial, and IT sectors showed the greatest coherence before the COVID-19 pandemic, which further increased during/after the pandemic confirming contagion in the US sectoral market. For the short-run investment period under bullish market conditions, we observed an increasing return coherence during/after the pandemic. The real estate, industrial, energy, and utilities sectors, which previously offered diversification due to low returns coherence, lost this potential during/after the COVID-19 period. This is in consent with financial contagion theory, which suggests that shocks in one market can rapidly spread to others, especially during crises (Forbes & Rigobon, 2002). Investors should therefore be aware that the sensitivity of the US sectoral market to crisis, both in general and COVID-19 in particular, is more pronounced for the short-run investment horizon. In the medium run under bearish and normal market conditions, the real estate and utilities sectors lost diversification potential during/after the COVID-19 period. While the real estate sector offers diversification opportunities during normal periods, it does not provide cover during the crisis. This corroborates the theory of time-varying market integration by Bekaert and Harvey, (1995) which suggests that the degree of market connectedness changes over time and is influenced by economic conditions. The returns coherence of the energy sector with other sectors remained weak during/after the COVID-19 period under extreme market conditions, offering optimal investment opportunities for hedging energy assets in a portfolio.

In the long run, we observed significant increases in US sectoral returns under optimistic market conditions during/after the COVID-19 period. Under normal market conditions, the real estate sector provided cover for the discretionary, financial, IT, and industrial sectors, while the energy sector acted as a hedger for all other sectors during/after the COVID-19 period. The findings for network connectedness revealed that before the COVID-19 period, the financial, utilities, and technology sectors played a dominant role in transmitting spillover toward other sectors. The materials sector was a major recipient of spillover from all sectors except the real estate sector. During the COVID-19 period, all sectors transmitted spillovers to the communications sector. This high level of spillover resulted from the global lockdown and the increased dependence on telecommunications for business continuity. In conclusion, our results highlight a significant shift in the coherence level among US sectoral returns during extreme market conditions particularly for the short-run investment horizon. Although an increase in the coherence level was also observed for the medium- and long-run investment horizons, the magnitude of this shift was less pronounced compared to the short-run. This finding matches with Zhang and Hamori (2021) who suggest that short-term spillovers are stronger than longer periods.

Our findings have significant practical implications, particularly in understanding sectoral contagion and resilience during calm and crisis periods. We highlight that coherence levels are higher during the short term compared to the medium and long-term periods during the COVID-19 pandemic. These results are in accordance with Zhang and Hamori (2021), and Mensi et al. (2022) who also suggest that short-term spillovers are stronger than longer periods. For short- and medium-term positions, the higher contagion risk in the real estate and utilities sector highlights their increased vulnerability during crises. This aligns with financial contagion theory suggesting that shocks in one market can rapidly spread to other markets, especially during crises (Forbes & Rigobon, 2002). Based on our results, we recommend reducing allocations to these sectors for short- and medium-term positions due to their high contagion risks and limited diversification benefits. In contrast, increasing holdings in the energy sector, particularly during COVID-19, is advisable, as it exhibits strong diversification potential with minimal dependency on other sectors.

For long-term investments, the energy sector's weak sensitivity to market fluctuations suggests combining it with discretionary, financial, IT, and industrial sectors to enhance risk-adjusted performance. From a risk management perspective, investors should consider more frequent rebalancing of short-term portfolios to adapt to the increased sector coherence observed during crises and establish lower adjustment correlation thresholds. These results corroborate previous research on commodity-equity linkages, such as Kilian & Park (2009) and Arouri et al. (2011), who highlighted the defensive nature of the energy sector and the return spillover between oil and equity markets. Similar conclusions have been drawn during COVID-19 by Salisu et al. (2019), Ashraf (2020); and Matos et al. (2021). Furthermore, Zhu et al. (2020), Szczygielski et al. (2021) and Sharif et al. (2024) reinforce our findings by demonstrating the energy sector's long-term hedging capabilities against market risks.

To further substantiate these findings theoretically, we have compared them with empirical studies. For instance, the increased sectoral coherence observed in our study is consistent with Vo & Hung (2021); Bouri et al. (2021), Shahzad et al. (2021), Mensi et al. (2023) who documented higher return connectedness across sectors during the pandemic. Rizvi et al. (2020) also identified sector-specific reactions to the COVID-19 pandemic, consistent with our observations. Our results also support the theory of time-varying market integration by Bekaert and Harvey, (1995) which suggests that the degree of market connectedness changes over time and is influenced by economic conditions.

Our findings have significant practical implications for market actors such as market policymakers/regulators, equity investors and portfolio managers. We highlight equity sector vulnerabilities and quantify the varied effects of the COVID-19 health crisis on U.S. stock returns. For investors, it is advisable to reduce allocations to real estate and utility sectors for short- and medium-term positions due to high contagion and weak diversification benefits. Instead, increasing holdings in the energy sector, especially during COVID-19 is advisable, underlying evidence of diversification ability, based on its least dependency on other sectors. For long-term investments, the weak sensitivity of the energy sector suggests combining it with discretionary, financial, IT, and industrial sectors as a hedge to enhance risk-adjusted performance. From the risk management perspective, portfolio managers should consider more frequent rebalancing of short-term portfolios to adapt to increased sector coherence and set lower correlation thresholds for adjustments during crises. Our study offers valuable insights for policymakers by identifying key sectors that transmit or absorb spillovers, guiding targeted support and regulatory measures to manage future stock pricing trajectories during crisis periods. Further, policy practitioners can infuse liquidity through bond purchases (Iwatsubo & Taishi, 2018) and offer competitive rates against short-term money markets. This resembles with the findings by Gomez-Gonzalez et al. (2020) who advocated that pandemic-related government policies significantly influenced stock market volatility in the US.

We acknowledge limitations in our study that open avenues for future research. By focusing solely on equity sectors we may have overlooked the potential flight-to-quality effects between stocks and fixed-income assets during the COVID-19 crisis, which could influence sectoral dynamics. The equity market reaction to COVID-19 is likely to differ across waves of the pandemic, each could lead to different outcomes and interpretations. Additionally, treating all sectors equally, without considering S&P 500 market capitalization weights, might have overstated the impact of smaller sectors. Furthermore, the primary focus of attention is on the U.S.-centric sample, limiting the relevance of our results to emerging markets. Future research should address these gaps by incorporating fixed-income assets to explore cross-asset dynamics, expanding the sample to include emerging markets for comparative analysis, and integrating key macroeconomic indicators and events to better understand the interplay between sectoral connectedness and broader economic trends throughout the crisis.

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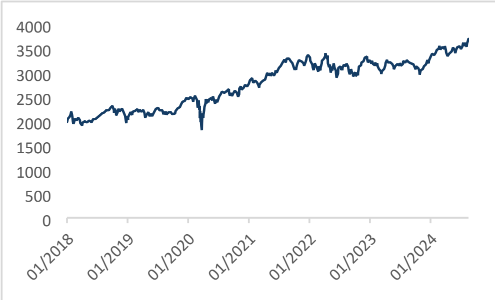
Table 1: Schematic connectedness table

	x_1	x_2	…	x_N	**Connectedness from others**
x_1	d^H_{11}	d^H_{12}	…	d^H_{1N}	$\sum_{J=1}^{N} d^H_{1j}, j \neq 1$
x_2	d^H_{21}	d^H_{22}	…	d^H_{2N}	$\sum_{J=1}^{N} d^H_{2j}, j \neq 2$
.	.	.	.	.	.
.	.	.	.	.	.
.	.	.	.	.	.
x_N	d^H_{N1}	d^H_{N2}	…	d^H_{NN}	$\sum_{J=1}^{N} d^H_{Nj}, j \neq N$
Connectedness to Others	$\sum_{\substack{i=1 \\ i\neq 1}}^{N} d^H_{i1}$	$\sum_{\substack{i=1 \\ i\neq 2}}^{N} d^H_{i2}$	…	$\sum_{\substack{i=1 \\ i\neq N}}^{N} d^H_{iN}$	$\frac{1}{N}\sum_{i,J=1}^{N} d^H_{iN}, i \neq N$

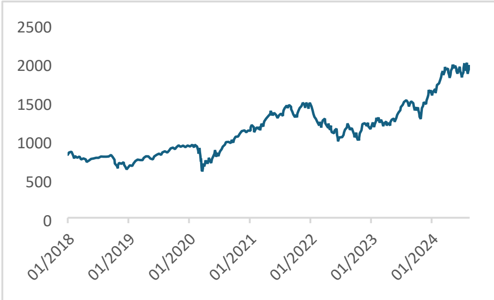
Table 2: Descriptive statistics

	Health Care	Consumer Material	Communication	Discretionary	Financial	Technology	Real Estate	Industrial	Energy	Utilities	S&P 500
Mean	0.0004	0.0005	0.0002	0.0004	0.0004	0.0008	0.0001	0.0003	0.0001	0.0002	0.0004
Maximum	0.0745	0.1079	0.0555	0.0710	0.1098	0.1090	0.0828	0.1155	0.1505	0.1215	0.0897
Minimum	-0.1065	-0.1527	-0.0900	-0.1131	-0.1009	-0.1461	-0.1809	-0.1318	-0.2275	-0.1225	-0.1277
Std. Dev.	0.0112	0.0155	0.0114	0.0139	0.0131	0.0169	0.0144	0.0136	0.0205	0.0131	0.0124
Skewness	-0.4590	-0.6485	-0.5965	-0.6964	-0.3075	-0.4449	-1.1967	-0.6514	-0.9886	-0.2698	-0.8206
Kurtosis	11.0843	9.5540	6.5397	6.4780	11.3921	6.6457	19.8746	13.6103	16.4059	17.5311	14.7959
JB Test	8938.04***	6717.37***	3194.21***	3173.40***	9404.27***	3249.55***	28945.7***	13505.25***	19725.5***	22222.4***	16009.6***
ADF	-12.6201***	-11.9058***	-11.0273***	-11.5842***	-12.0552***	-11.6536***	-11.6243***	-11.4895***	-11.3008***	-12.1052***	-11.5319***
PP	-1940.03***	-1810.07***	-1752.98***	-1940.99***	-1981.32***	-1947.25***	-1933.47***	-1913.26***	-1923.33***	-1861.22***	-2055.99***
KPSS	0.0223	0.1030	0.1238	0.0616	0.0666	0.0669	0.0380	0.0418	0.1603	0.0218	0.0490
Q(20)	3012.56***	1738.78***	1221.42***	1592.41***	2023.34***	1458.78***	1504.00***	2609.14***	1218.82***	3778.29***	2508.61***
ARCH(20)	237.222***	80.7526***	100.1763***	127.389***	174.193***	154.681***	140.606***	232.089***	114.782***	239.221***	292.994***

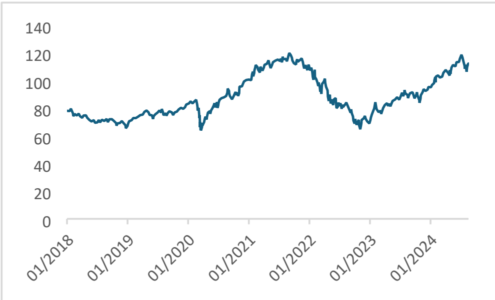
Notes: ***,**,* represents significance at 1, 5, 10 percent respectively.



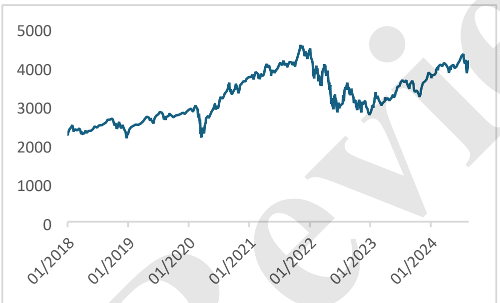
a) Healthcare



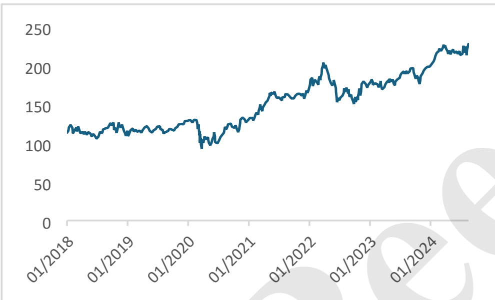
b) Consumer Materials



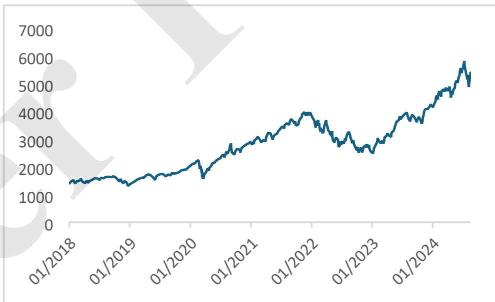
c) Communications



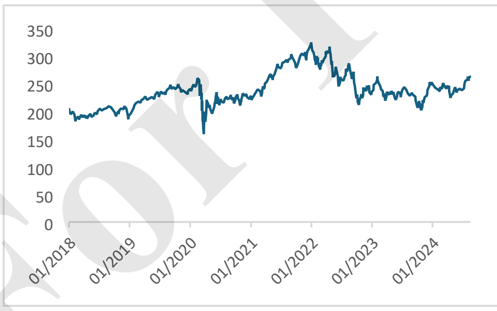
d) Consumer Discretionary



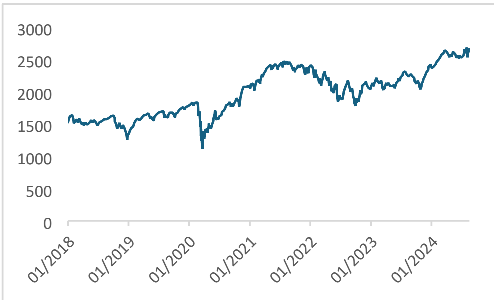
e) Financials



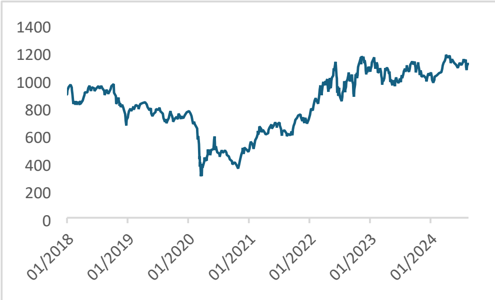
f) Technology



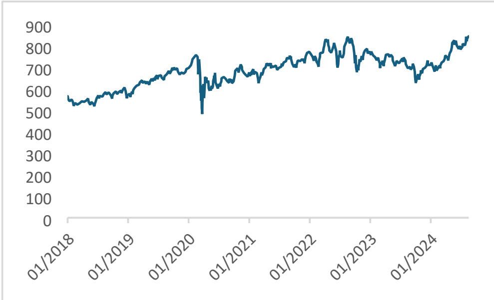
g) Real Estate



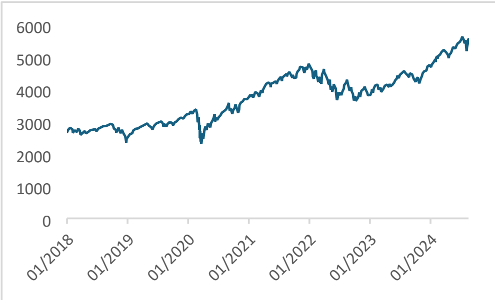
h) Industrials



i) Energy

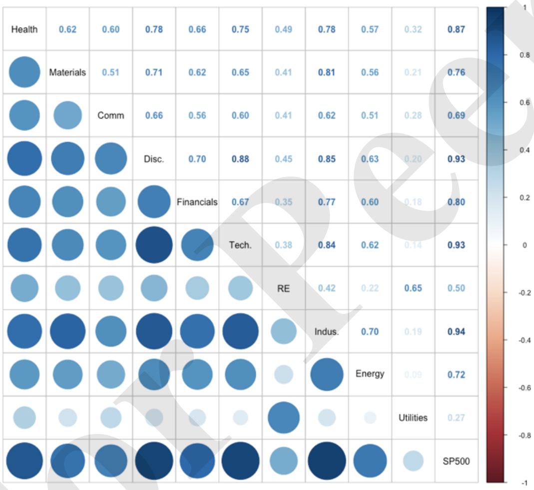


j) Utilities

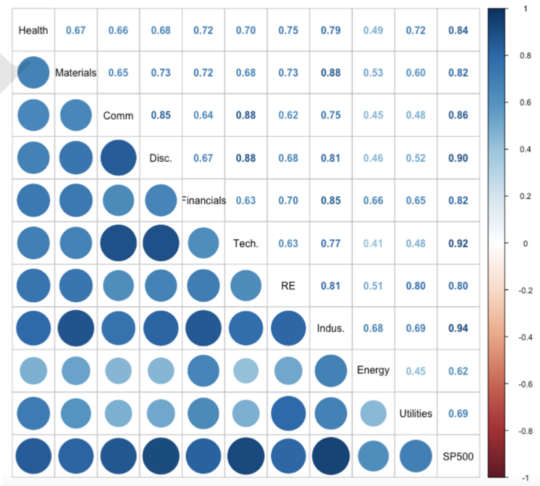


k) S&P 500

Figure 1: US sectoral pricing trend



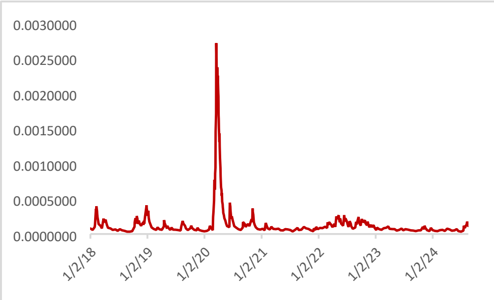
Pre-COVID-19



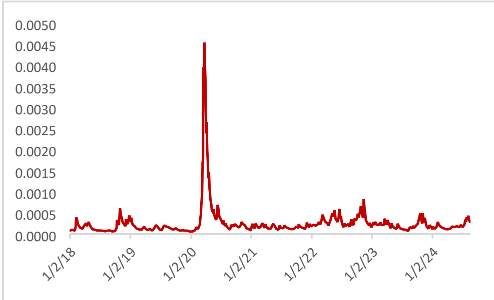
Post-COVID-19

Figure 2: Pre- and post-COVID-19 correlation analysis

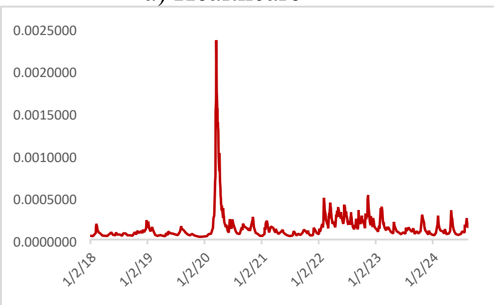
Notes: In the above figure, magnitude of correlation ranges from -1 (strongly negative) to 1 (strongly positive). This magnitude of correlation is presented by the colour meter at the right side of both the figures. The shape of correlation between two sectors changes from circle to ellipse as the magnitude of correlation strengthens.



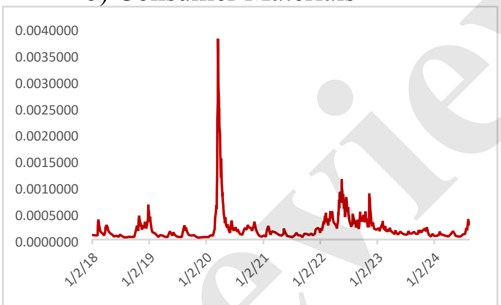
a) Healthcare



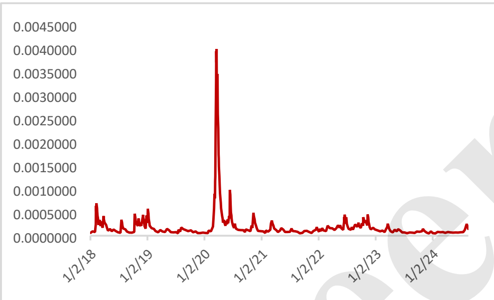
b) Consumer Materials



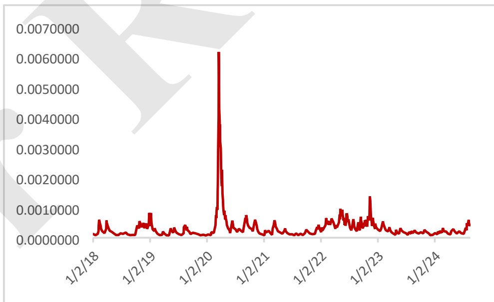
c) Communications



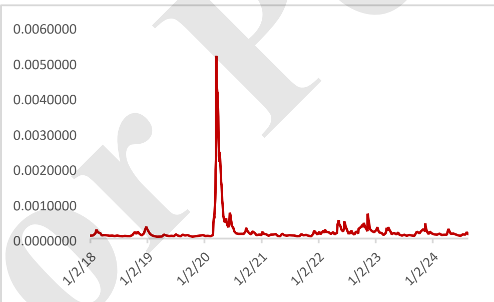
d) Consumer Discretionary



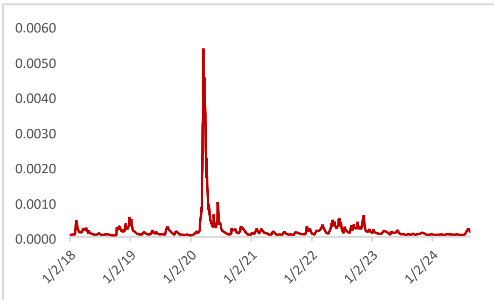
e) Financials



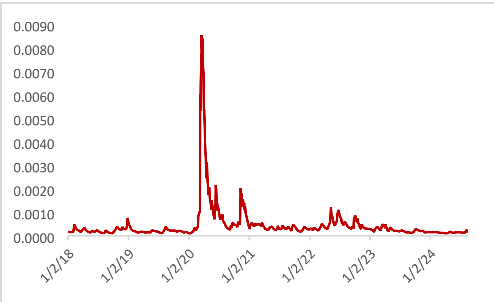
f) Technology



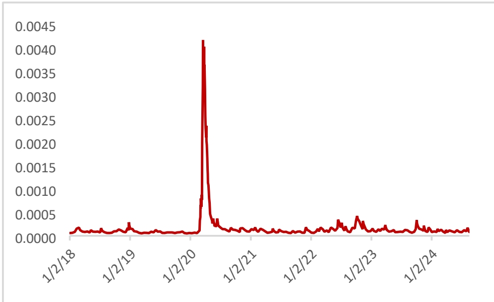
g) Real Estate



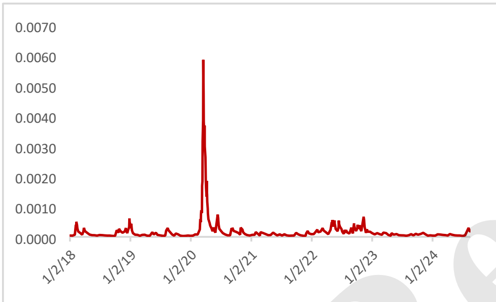
h) Industrials



i) Energy



j) Utilities



k) S&P 500

Figure 3: Volatility analysis

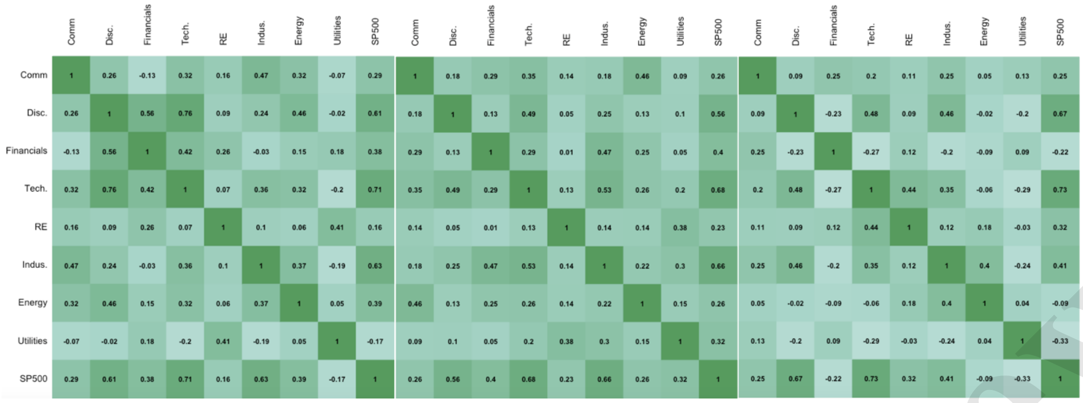


Figure 4a: Pre-COVID19 cross-spectral short-run analysis

Notes: The above figure present results of quantile cross-spectral between different US sectoral returns. The magnitude of cross-spectral ranges from light purple to dark purple colour. Notably, quantile cross-spectral between any two sectors is asymmetric in nature and the values across both sides of the diagonal differ from each other.

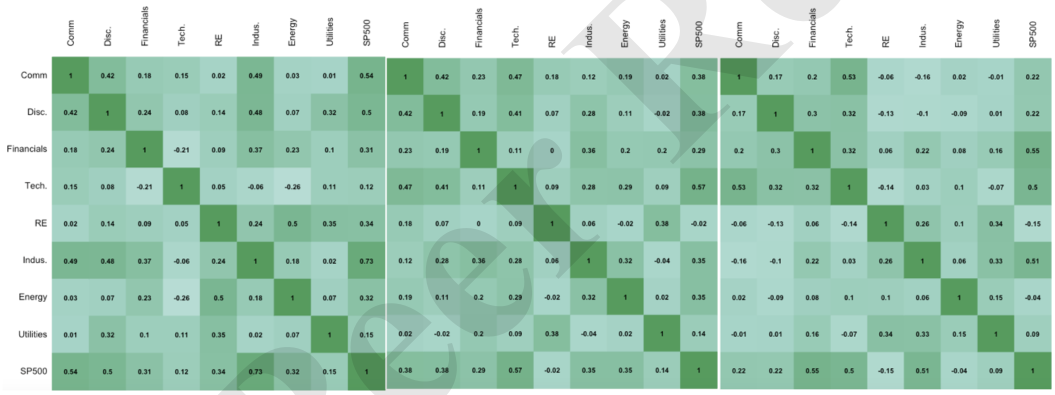


Figure 4b: COVID19 cross-spectral short-run analysis

Notes: Similar to Figure 4a

Figure 5a: Pre-COVID19 cross-spectral medium-run analysis

Notes: Similar to Figure 4a

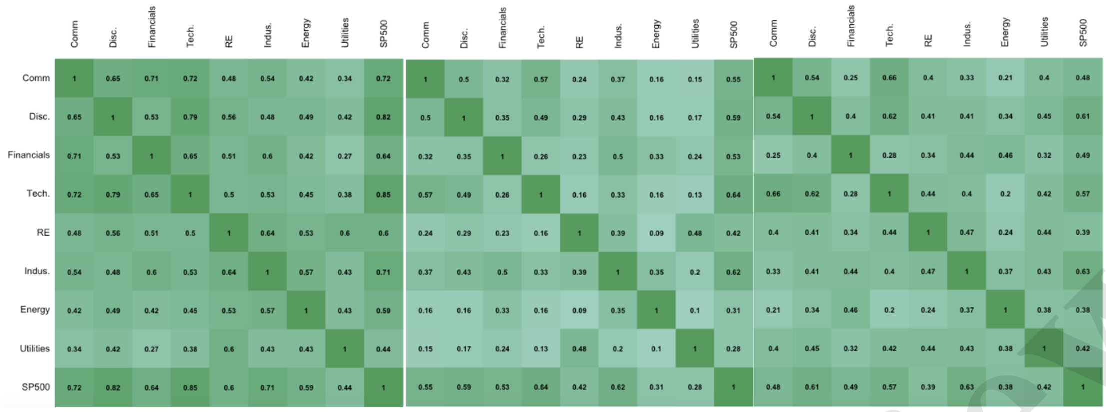


Figure 5b: COVID19 cross-spectral medium-run analysis

Notes: Similar to Figure 4a

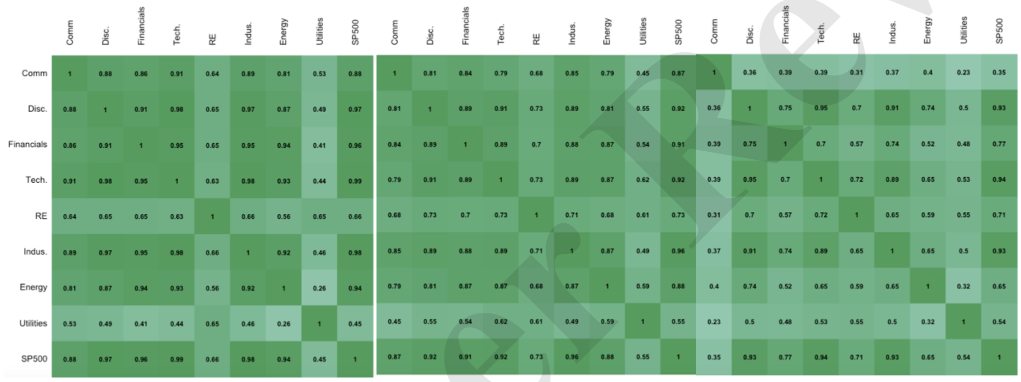


Figure 6a: Pre-COVID19 cross-spectral long-run analysis

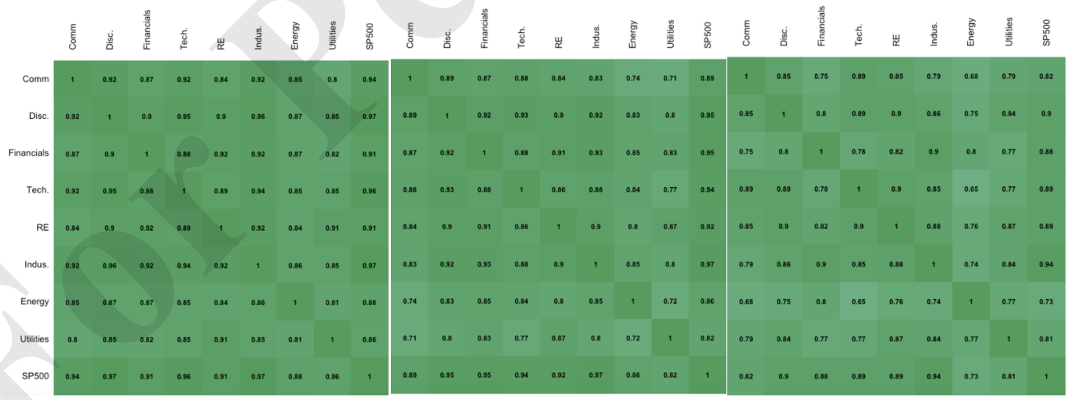


Figure 6b: COVID19 cross-spectral long-run analysis

Notes: Similar to Figure 4a

Figure 7a: Network connectedness complete sample

Notes: The network connectedness in Figure 7a are based on the results of Diebold and Yilmaz (2014) spillover approach. The size of the nodes represents their transmission and reception effect. The colour of the nodes shows the strength of spillover. Dark blue colour highlight strong connectedness whereas light blue colour shows weak connectedness. The arrow head of the edges represents direction of connectedness.

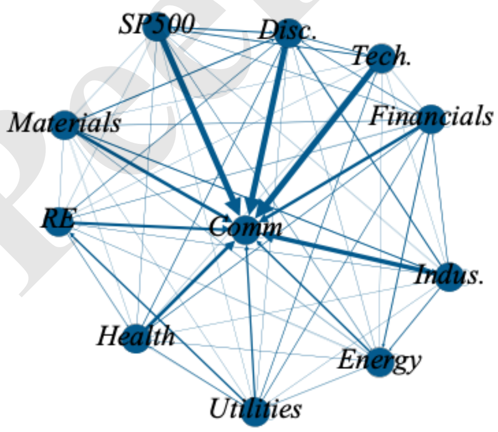


Figure 7b: Network connectedness pre-COVID19

Notes: Similar to Figure 7a.

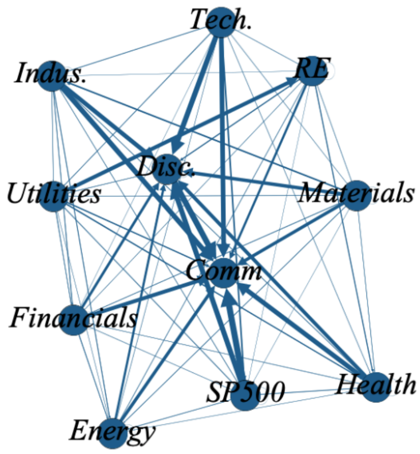


Figure 7c: Network connectedness post-COVID19

Notes: Similar to Figure 7a.

Appendix

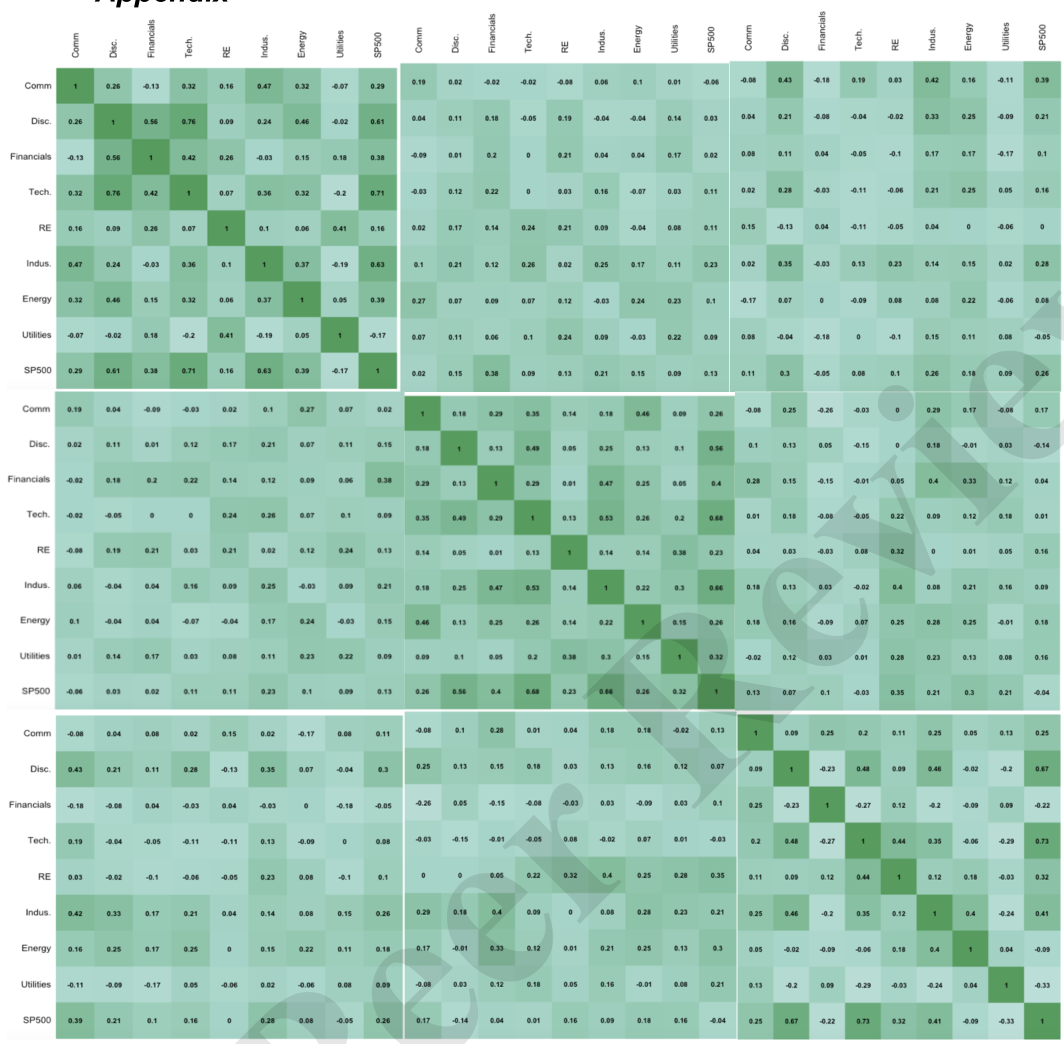


Figure A1: Pre-COVID19 cross-spectral short-run analysis

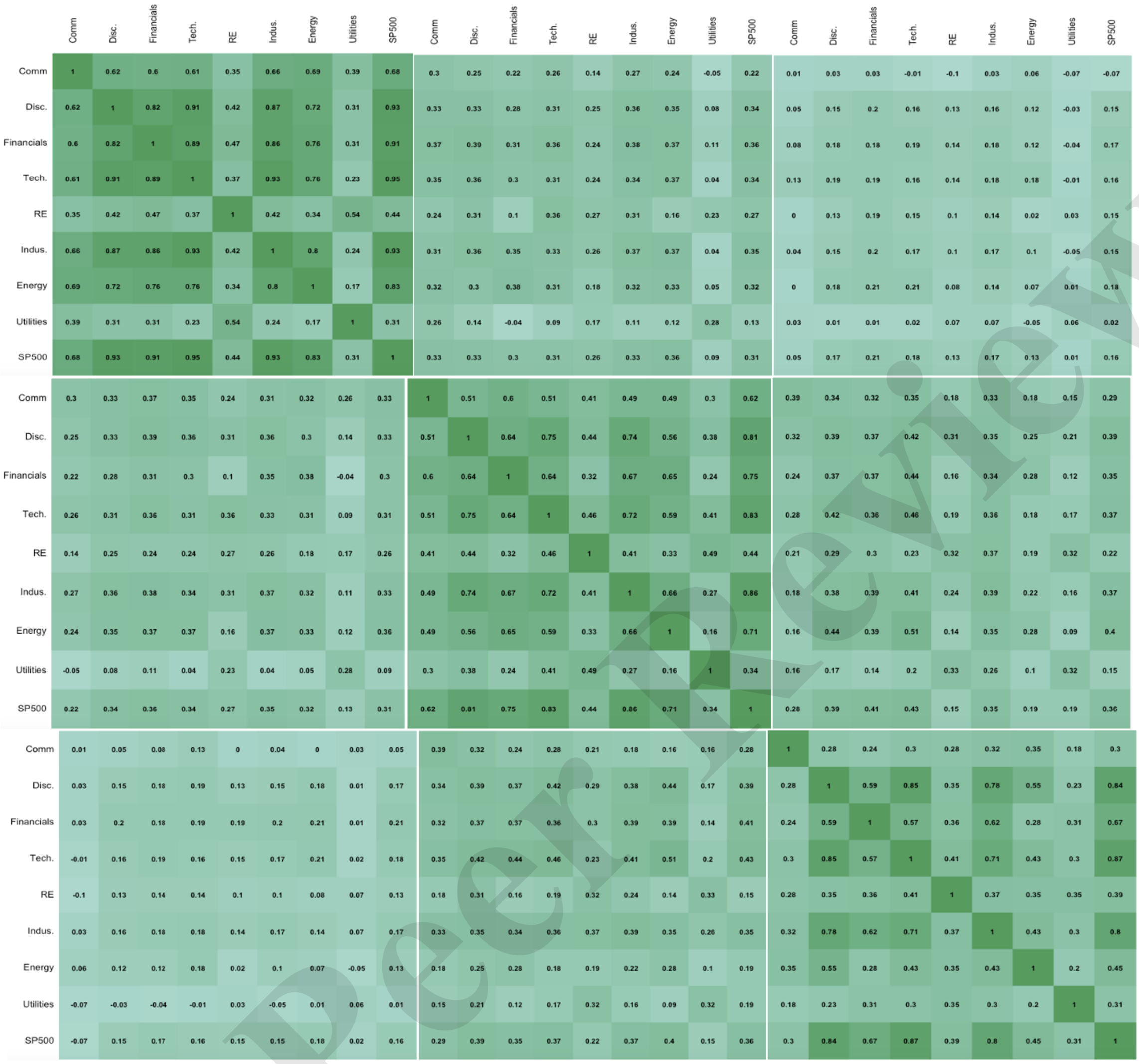


Figure A2: Pre-COVID19 cross-spectral medium-run analysis

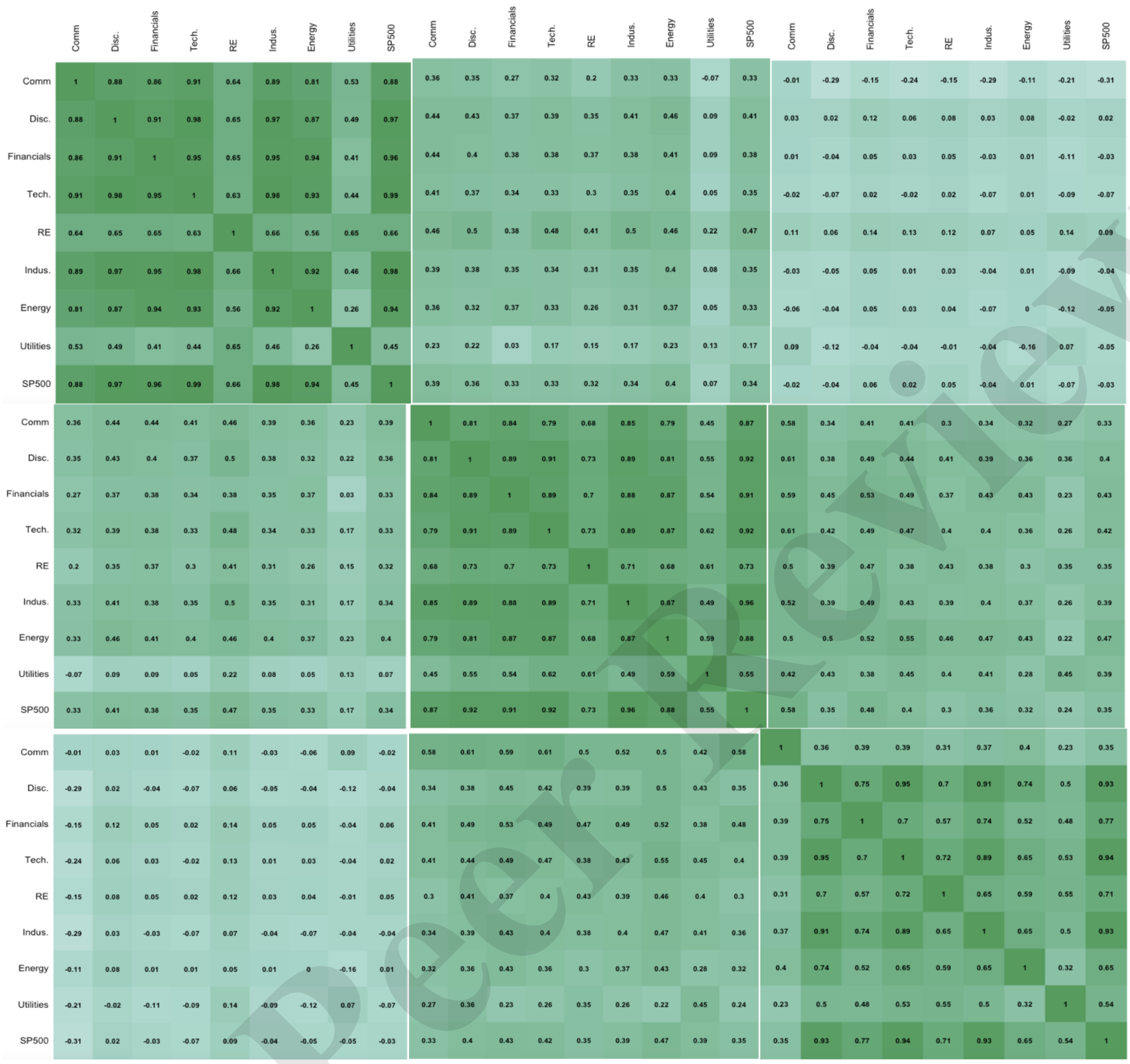


Figure A3: Pre-COVID19 cross-spectral long-run analysis

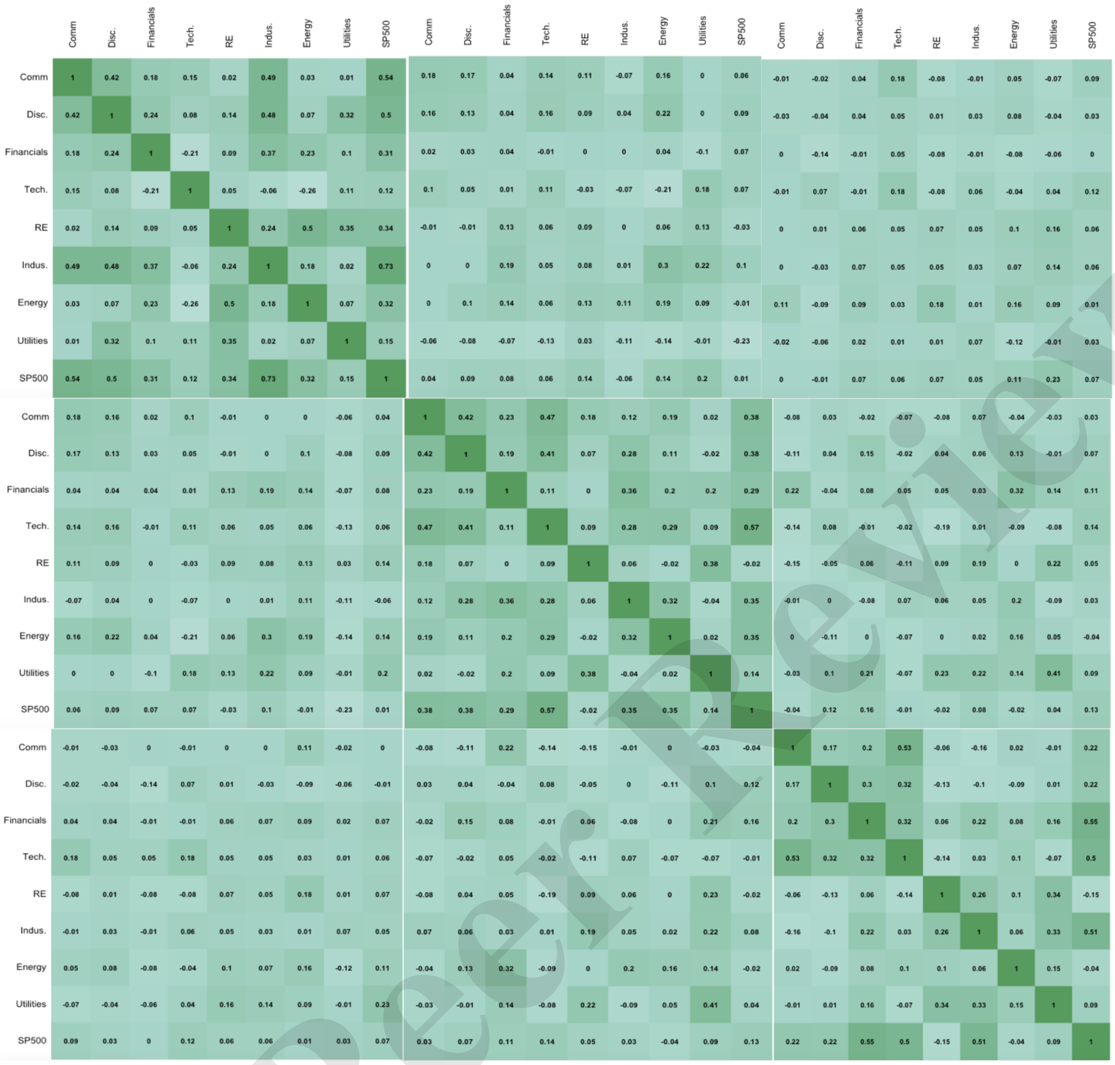


Figure A4: COVID19 cross-spectral short-run analysis

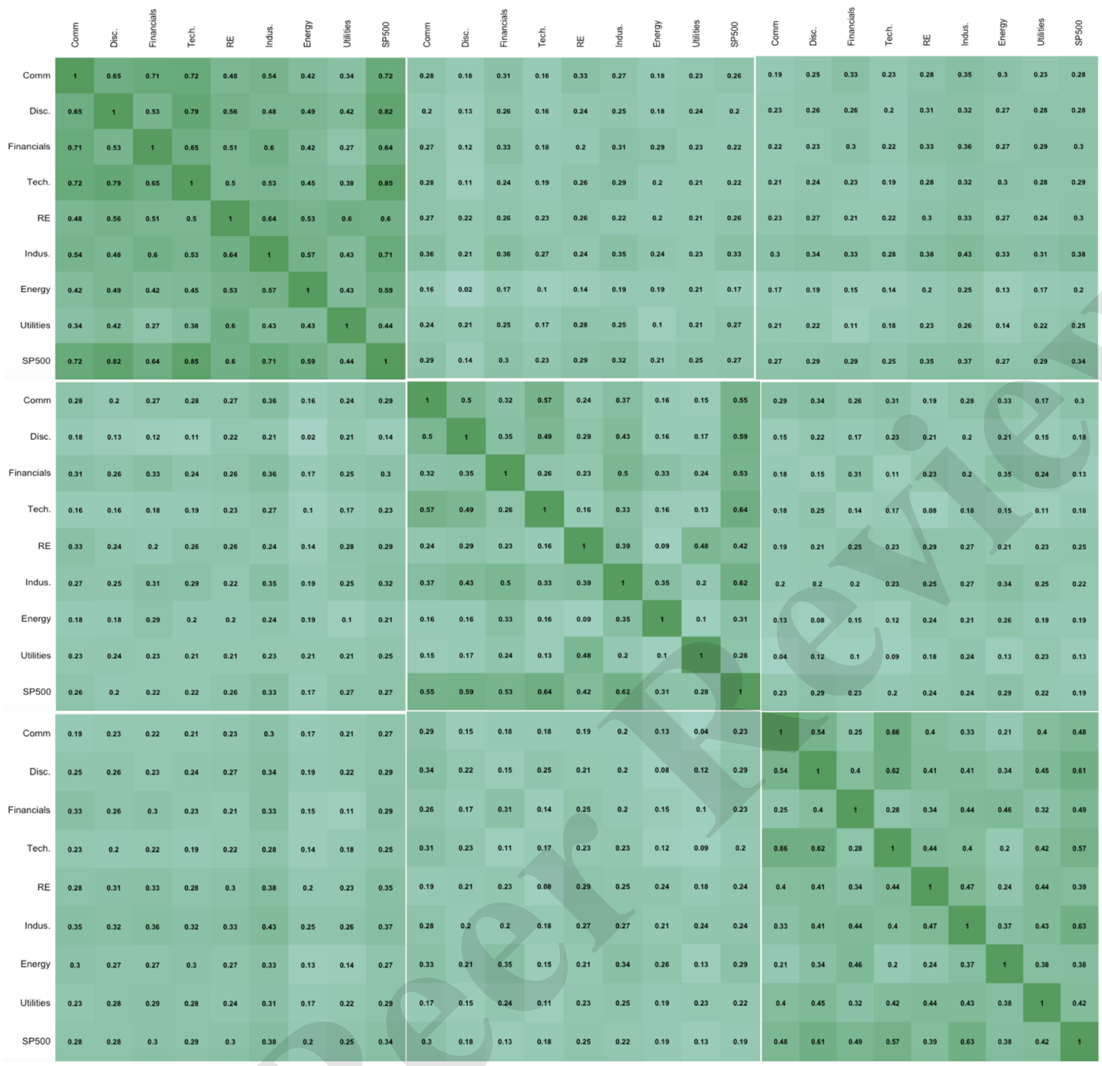


Figure A5: COVID19 cross-spectral medium-run analysis

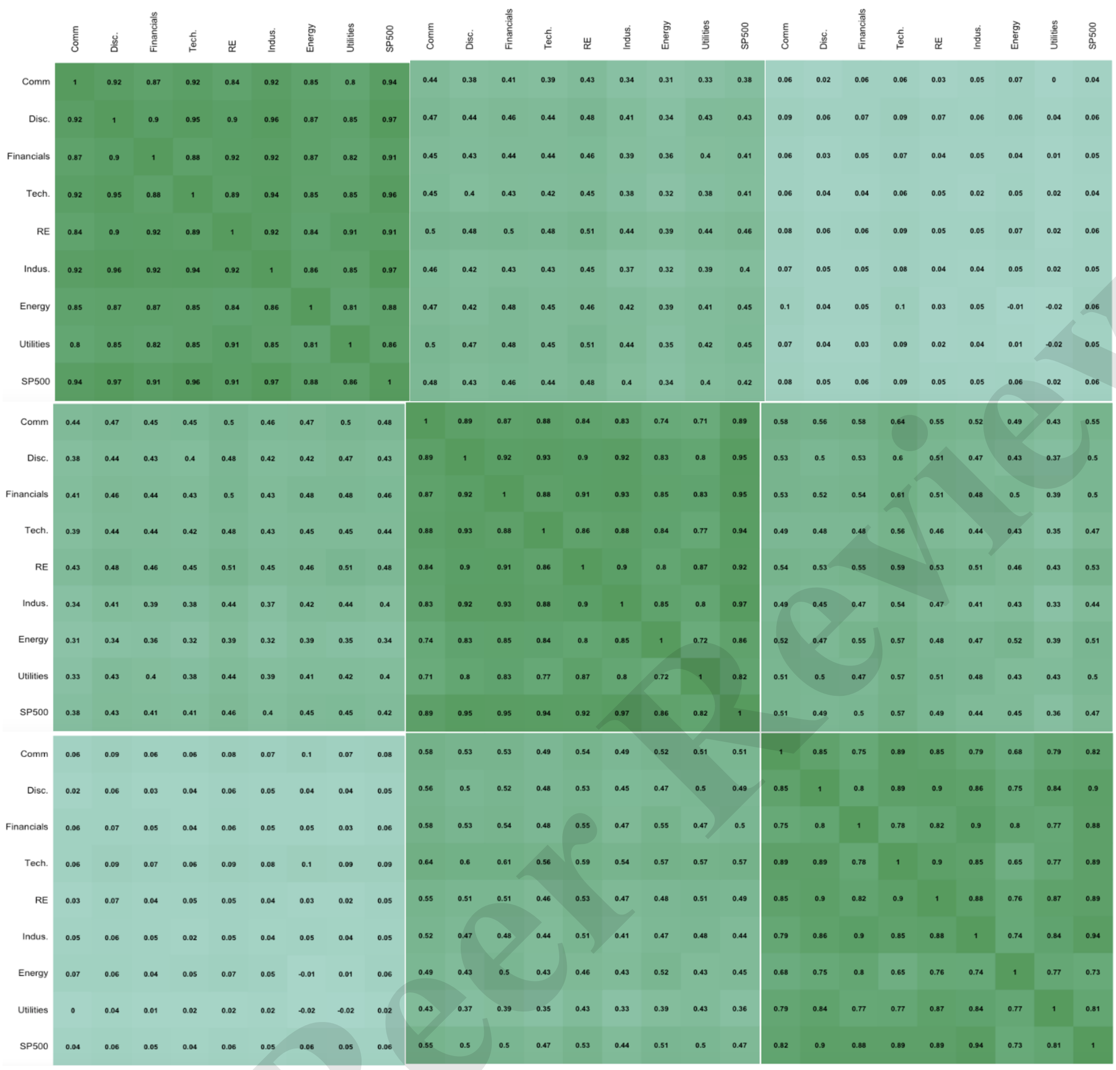


Figure A6: COVID19 cross-spectral long-run analysis