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Co-movements in sector price indexes during the COVID-19 crisis: Evidence from the US

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ARTICLE INFO

Keywords:
COVID-19
Sector index co-movements
Contagion
Vector error correction model, healthcare sector index

ABSTRACT

This paper is an examination of co-movements between sector indexes in the United States prior to and during the COVID-19 period. Using daily data between January 2013 and July 2020, this study is the first to examine sectoral cointegration, as well as how contagion occurs from one healthcare sector to others. We find that only five sectors reacted to the shock to the healthcare sector. Our findings can assist policymakers in appropriately responding to the current crisis and tackling potential pandemics in the future. Our findings are also valuable for stockholders in terms of predicting price changes and improving portfolio diversification.

1. Introduction

In recent years, financial crises have multiplied, which has affected the evolution and connection of stock markets. Several studies on the contagion phenomenon have explored co-movement between sectors during periods of crisis. For instance, Phylaktis and Xia (2009) highlighted the advantages of the sectoral contagion phenomenon that provides some benefits of international diversification during crises. Similarly, Baur (2012) examined co-movement between the financial sector and the other real economy sectors in twenty-five major stock markets during the subprime crisis. Notably, the study found that all sectors and countries were exposed to adverse effects of the crisis, although some sectors (i.e., healthcare, telecommunications, and technology) realized only minor impacts. The current global COVID-19 health crisis has increased stock price co-movements, severely affecting the financial system. In response, a growing body of literature has examined the effects of COVID-19 on stock market returns (M. Akhtaruzzaman et al., 2021; Mazur et al., 2021; Topçu and Gulal, 2020; Zhang et al., 2020). These researchers employ various methods to investigate the link between the COVID-19 breakdown and global financial market performance. Other researchers have explored the effect of contagion on various asset classes—such as oil, gold, and cryptocurrency—as safe havens or hedges during the COVID-19 pandemic(Akhtaruzzaman et al., 2020a; Akhtaruzzaman et al., 2020b; Corbet et al., 2020; Devpura and Narayan, 2020; Gharib et al., 2021; Gunay, 2020; Mensi et al., 2020; Salisu et al., 2020, 2021; Sharif et al., 2020). Interestingly, the sectoral dimension of the COVID-19 pandemic has been illustrated by several recent empirical studies (Baek et al., 2020; Hanif et al., 2021; Rizwan et al., 2020), but only M. Akhtaruzzaman et al. (2021) and Shahzad et al. (2021) have focused on the connection between sector indexes during the COVID-19 period.

Furthermore, to the best of our knowledge, these studies have not examined sectoral co-movements by focusing specifically on the
healthcare sector as the source of sectoral contagion during the COVID-19 outbreak. This study aims to fill this knowledge gap and use cointegration analysis to examine the shock of the healthcare sector to other sectors. In practice, the healthcare sector plays a vital role in the global economy Chen (2016). However, the analysis of co-movement between healthcare sectors and other sectors is not widely explored in the current body of literature. In this context, studies by Chen et al. (2015, 2017) confirm the importance of the dual issues of contagion and the healthcare sector. Specifically, they examined the dynamic relationship of returns in the healthcare sector among different stock markets (the US, UK, and Germany) using the continuous wavelet approach. Our work contributes to the literature in two ways: While most COVID-19-related finance research has studied the crisis effects on sectoral performance or risk, we explored the co-movements between the healthcare sector and other industries before and during the COVID-19 crisis. Moreover, we identify the most cointegrated sector indexes and explain their relationship with the healthcare sector.

The study highlights two main findings: First, we find evidence of five relationships between sectors during the COVID-19 crisis. Second, we show that contagion occurs from one healthcare sector to five other sectors. The results indicate that the healthcare sector price is an important indicator that can assist policymakers in developing early economic and healthcare policy responses, especially during this unprecedented pandemic. This finding is consistent with the existing literature (Barro, 2013; Koijen et al., 2016; Sala-i–Martin et al., 2004), suggesting that the healthcare industry is an important determinant of economic growth, making it a very attractive sector for investors (Allen, 2021). However, our results differ significantly from Akhtaruzzaman et al., 2021b, who demonstrate the central role of financial institutions while using a dynamic cross-correlation analysis, and Shahzad et al. (2021), who use network analysis to examine the interaction between sector indexes and highlight the central role of the IT sector.

This paper is organized into four major sections. Section 2 describes the data and provides descriptive statistics. Section 3 outlines and discusses our empirical results. Finally, Section 4 summarizes the main conclusions of this study.

2. Data and preliminary analysis

2.1. Data

We use daily data of the main sectoral index prices in the US: energy, materials, industrial (INDUST), consumer discretionary (CONS_DISCR), consumer staples (CONS_STAPLES), healthcare (HEALTH), financials, information technology (IT), communication services (COM_SERVICE), utilities, and real estate.¹ The healthcare index is considered as the benchmark index to evaluate sectoral contagion before and during the COVID-19 period.

Data were collected from DataStream. We divide our sample period into two sub-periods: the pre-COVID-19 period (January 1, 2013–January 22, 2020) and the COVID-19 period (January 23, 2020–July 29, 2020). We started in January 2013 to avoid overlapping with the great recession of 2007–2012. On the other hand, we choose the start date of the COVID-19 period as the date of the first confirmed case reported by the World Health Organization.

We apply the following empirical methodology: first, we check for multivariate cointegration using Johansen’s cointegration model (1988), and conduct a bivariate cointegration analysis to measure co-movements between the healthcare sector and other sectors. Once we detected the cointegration relationships, we moved to the estimation of a vector error correction model (VECM) for each cointegrated pair of sectors. Finally, we test the short- and long-run Granger causality in the VECM between sector indexes.

2.2. Descriptive statistics

Table 1 presents the descriptive statistics of the daily index prices of the 11 sectors used in this study. From this table, we can see that the average price index of all sectors increased during the COVID-19 crisis, except in the energy sector. The latter recorded an increase in its standard deviation, suggesting an increase in volatility. In contrast, we observe that the volatility of all other sectors decreased during the pandemic period. Fig. 1 shows that the most important decline in stock prices in all sectors occurred between February and March 2020. Furthermore, the kurtosis values are different from 3, which means that the distributions are leptokurtic. Moreover, the skewness values are different from 0, so the distributions are not skewed. This implies that the normality assumption is rejected for all series.

To conduct a cointegration analysis, it is necessary to check whether the series of stock prices meets two conditions: non-stationarity and having the same order of integration. Thus, we applied different tests: the augmented Dickey–Fuller test (ADF) test, the Philips–Perron (PP) test, and the Kwiatkowski –Phillips–Schmidt–Shin (KPSS) test. Tables 2 and 3 present the results of the stationarity tests. We found that all series are non-stationary in level, and we tested the stationarity of the series in the first difference, where the results indicate that our series is I (1). Therefore, we can apply cointegration tests using Johansen’s cointegration model (1988).

2.3. Correlation analysis between the healthcare sector and other sectors

We note that during the COVID-19 period, correlations increased with some sectors and decreased with others, which reflects signs of sectoral contagion (Table 4).

¹ We chose sector classification according to the Global Industry Classification Standard structure (GICS). https://www.msci.com/gics
Table 1
Summary Statistics.

| Sectoral index prices: Pre-COVID-19-period (January 1, 2013–January 22, 2020) |
|---------------------------------|---------------------------------|---------------------------------|---------------------------------|---------------------------------|---------------------------------|---------------------------------|---------------------------------|---------------------------------|---------------------------------|---------------------------------|---------------------------------|
| COM_SERVICE | CON_DISC | CON_STAPLES | ENERGY | FINANCIALS | HEALTH | INDUST | IT | MATERIALS | REAL_ESTATE | UTILITIES |
| Mean          | 95.193    | 316.359     | 312.945 | 407.989    | 312.76  | 341.51  | 237.181 | 343.046 | 491.437 | 285.647 |
| Median        | 95.32     | 292.65     | 321.7   | 400.86    | 160.75  | 319.43  | 197.61  | 330.62  | 492.8   | 284.67  |
| Maximum       | 138.41    | 498.9      | 534.89  | 353.8     | 272.98  | 497.71  | 477.52  | 450.76  | 716.62  | 443.62  |
| Minimum       | 70.53     | 166.73     | 196.37  | 290.35    | 103.07  | 198.13  | 116.43  | 235.87  | 336.16  | 181.58  |
| Std. Dev.     | 13.962    | 53.218     | 43.414  | 44.509    | 71.412  | 88.937  | 56.857  | 90.141  | 60.688  | 181.58  |
| Kurtosis      | 0.637     | 0.363      | 0.073   | 0.517     | 0.259   | 0.085   | 0.16    | 0.043   | 0.446   | 0.379   |
| Jarque-Bera   | 125.086   | 115.256    | 39.41   | 93.289    | 151.479 | 42.722  | 161.765 | 101.124 | 69.436  | 76.765  |
| Sum           | 175,440.6 | 583,050.4  | 576,757.6 | 751,923.9 | 333,736.1 | 629,402.1 | 437,123.6 | 632,233.2 | 905,717.7 | 526,446.5 |
| Sum.Sq.Dev.   | 359,051   | 13,406,219 | 5,216,773 | 3,471,700 | 3,649,172 | 9,393,527 | 10,532,553 | 14,569,908 | 14,966,916 | 6,786,277 |

| Sectoral index prices: COVID-19-period (January 23, 2020–July 29, 2020) |
|---------------------------------|---------------------------------|---------------------------------|---------------------------------|---------------------------------|---------------------------------|---------------------------------|---------------------------------|---------------------------------|---------------------------------|---------------------------------|---------------------------------|
| COM_SERVICE | CON_DISC | CON_STAPLES | ENERGY | FINANCIALS | HEALTH | INDUST | IT | MATERIALS | REAL_ESTATE | UTILITIES |
| Mean          | 126.8204  | 490.7027   | 403.0807 | 255.9677  | 451.536 | 411.9482 | 463.786 | 392.9745 | 625.6058 | 391.9844 |
| Median        | 130.57    | 496.555    | 402.5   | 246.7     | 206.725 | 459.525  | 412.93  | 473.05  | 401.18  | 625.31  |
| Maximum       | 141.21    | 598.92     | 438.46  | 362.99    | 274.98  | 496.67   | 503.44  | 542.38  | 456.27  | 749.58  |
| Minimum       | 99.21     | 349.35     | 330.74  | 153.4     | 154.1   | 341.62   | 293.81  | 343.59  | 278.51  | 449.99  |
| Std. Dev.     | 11.24657  | 61.16602   | 21.74034 | 50.747    | 30.38693 | 30.97916 | 49.10671 | 49.19097 | 42.30074 | 64.65905 |
| Kurtosis      | 0.805972  | 0.37594    | 0.617415 | 0.528358  | 0.743153 | 0.180243 | 0.050109 | 0.053923 | 0.024206 | 0.296267 |
| Jarque-Bera   | 11.24657  | 61.16602   | 21.74034 | 50.747    | 30.38693 | 30.97916 | 49.10671 | 49.19097 | 42.30074 | 64.65905 |
| Sum           | 16,993.94 | 65,754.16  | 54,012.82 | 34,299.68 | 28,686.04 | 60,505.83 | 55,201.06 | 52,658.58 | 83,831.18 | 52,525.91 |
| Sum.Sq.Dev.   | 16,822.56 | 497,959.06 | 62,861.45 | 342,509.3 | 122,807.6 | 127,641.2 | 320,725.4 | 321,827 | 237,983.9 | 556,045.5 |

Notes: Our sample contains daily data. The period sample is divided into two sub-periods, where the pre-COVID-19 period is from 1 January 2013 to 22 January 2020 and the COVID-19 period is from 23 January 2020 to 29 July 2020.

Jarque–Bera statistic tests for the null hypothesis of Gaussian distribution.
However, this analysis did not consider the temporal variability of interdependence. Therefore, we use the dynamic conditional correlation (DCC) model developed by Engle (2002). The author proposes a new class of multivariate GARCH estimators, which is a generalization of the Bollerslev (1990) constant conditional correlation (CCC) estimator. The dynamic correlation model allows the matrix correlation to be time-varying.

Fig. 2 shows the time-varying correlation between the healthcare sector and other sectors during the entire period (from January 1, 2013, to July 29, 2020). The results of the DCC show that the healthcare sector is correlated with other sectors during the COVID-19 period.
There is considerable interdependence between these sectors and the healthcare sector, as shown in Fig. 2. Indeed, the correlation between these sectors accelerated throughout the post-crisis period. We can observe that the cross-correlations of index returns are dynamic and show upward trends related to crisis events. Therefore, the dynamic correlation estimates confirm the varying and volatile interdependencies between the sectors. After estimating the time-varying correlation, we apply cointegration tests to measure the level of this interdependence and to specify a common long-term trend.

3. Empirical results and discussion

3.1. Testing for multivariate cointegration

Johansen’s multivariate cointegration test among the US sectors reveals the existence of a single long-run cointegration relationship before the COVID-19 period (see Table 5). These sectors were not integrated before the crisis. However, the cointegration results show evidence of five relationships between sectors during the COVID-19 crisis, which can be explained by the contagion effect. These results prove that the markets are integrated. Furthermore, these cointegrating relationships between sector indexes reflect their convergence toward a certain stable equilibrium level over the long term.
Table 4

Correlation analysis between the health care sector and other sectors.

|                      | COM_SERVICE | CONS_DISCR | CONSSTAPLES | ENERGY | FINANCIALS | INDUST | IT  | MATERIALS | REAL_ESTATE | UTILITIES |
|----------------------|-------------|------------|-------------|--------|------------|--------|-----|-----------|-------------|-----------|
| Pre-COVID-19-period  | 0.875       | 0.970      | 0.951       | -0.313 | 0.944      | 0.957  | 0.952| 0.917     | 0.932       | 0.942     |
| COVID-19-period      | 0.915       | 0.910      | 0.795       | 0.565  | 0.503      | 0.651  | 0.907| 0.896     | 0.579       | 0.511     |

**Note:** the above table contains the Pearson correlation coefficients between health care sector and the other sectors before and during COVID-19 period.
3.2. Testing for bivariate cointegration

The healthcare index is considered the benchmark index to evaluate co-movements and the integration of other sector indexes in relation to the healthcare sector index. The bivariate cointegration test between the healthcare sector and the other sectors showed the absence of a stable equilibrium relationship before the health crisis, and hence their segmentation.

Fig. 3 shows the response of the sectors to one standard deviation shock to the healthcare sector. We observe that the standard deviation shock to the healthcare index has a noticeable impact on all sectors from the first period. These responses sharply decline until period 2 and then gradually increase.

However, the bivariate cointegration test during the COVID-19 period indicated five relationships between the healthcare index and the other sector indexes. Indeed, we did not reject the cointegration hypothesis for five pairs: health-communication services, health-consumer discretionary, health-financials, health-industrials, and health-materials (see Table 6), highlighting co-movements around a common tendency for the stock prices of these sectors.

Regarding the communication services and the consumer discretionary sector, the cointegration with the healthcare sector can be explained by two points: first, the increasing demand for communication tools during the confinement, and second, the rise in discretionary expenses resulting from the lockdown and possible rise in the level of savings of households. Regarding materials, the market saw an important rise in some safe-haven assets such as gold, or essential mining materials, such as copper, due to supply shortages and lockdowns. Concerning the industrial and financial sectors, they both registered a sharp decline during confinement and then started to rise slowly.

Therefore, the birth of new relationships with the healthcare industry in response to the COVID-19 crisis reflects the contagion’s
Table 5
Testing for multivariate cointegration.

|                  | Pre-COVID-19-period (January 1, 2013-January 22, 2020) | COVID-19-period (January 23, 2020-July 29, 2020) |
|------------------|--------------------------------------------------------|-------------------------------------------------|
| Null hypothesis | J trace       | J max                                         | J trace       | J max                                         |
| r = 0            | 303.7518*    | 66.2009                                       | 387.2194*    | 92.8011*                                      |
| r = 1            | 237.5508     | 64.5047                                       | 294.4183*    | 69.6266*                                      |
| r = 2            | 224.7917*    | 52.1832                                       | 172.6084*    | 43.0205                                       |
| r = 3            | 172.6084*    | 39.5865                                       | 129.5879*    | 34.3672                                       |
| r = 4            | 129.5879*    | 34.3672                                       | 90.0014      | 34.3672                                       |
| r = 5            | 90.0014      | 34.3672                                       | 90.0014      | 34.3672                                       |

Notes: J Trace and J max indicate the statistics of Johansen’s cointegration model (1988). Rejection of the null hypothesis of no cointegration at the 5% is denoted by *.

![Response to Cholesky One S.D. (df. adjusted) Innovations ± 2 S.E.](image)

Fig. 3. Impulsive response of sectors during COVID-19 period. Notes: The blue lines show the impulsive response of each sector index to the one standard deviation shock to health during the COVID-19 period (from January 23, 2020, to July 29, 2020), while the red lines indicate the 95 percent confidence interval.
occurrence from the healthcare sector to other sectors. This finding indicates the importance of the healthcare sector’s impact on the progress of society as a whole Chen (2016). The findings of this study align with those of Chen et al. (2017), who highlight the role of healthcare stock as a predictor of short and long stock prices.

The results of the bivariate cointegration test enabled us to estimate the VECM for each of the above pairs of sectors. The analysis of the VECM estimation yielded two interesting results: first, we noticed the presence of a significant and negative adjustment term for all pairs under question, and second, the value of the adjustment term is significantly higher for the financial sector, suggesting a rapid mean reversion toward the healthcare sector during the COVID-19 crisis.

Table 6 shows the short-and long-run bidirectional relationships between industrial and consumer discretionary. On the other hand, there are short-and long-run relationships between healthcare and financials. Regarding materials and healthcare, we notice short-and long-run unidirectional relationships.

| Table 6 | Testing for bivariate cointegration during COVID-19-period. |
| --- | --- |
| HEALTH - COMMUNICATION_SERVICES |  |
| Null hypothesis | J trace | J max |
| $r = 0$ | 17.3578* | 13.1019 |
| $r = 1$ | 4.2559* | 4.2559* |
| HEALTH - CONS_DISCR |  |
| Null hypothesis | J trace | J max |
| $r = 0$ | 17.8316* | 17.2738* |
| $r = 1$ | 0.55781 | 0.5578 |
| HEALTH - FINANCIALS |  |
| Null hypothesis | J trace | J max |
| $r = 0$ | 16.4954* | 12.7269 |
| $r = 1$ | 3.7685 | 3.7685 |
| HEALTH - INDUSTRIALS |  |
| Null hypothesis | J trace | J max |
| $r = 0$ | 16.1833* | 9.6312 |
| $r = 1$ | 6.5521* | 6.5521 |
| MATERIALS- HEALTH |  |
| Null hypothesis | J trace | J max |
| $r = 0$ | 17.0040* | 12.4725* |
| $r = 1$ | 4.5315* | 4.5316* |

Notes: J Trace and J max indicate the statistics of Johansen’s cointegration model (1988). Rejection of the null hypothesis of no cointegration at the 5% is denoted by *.

Table 7 shows the short-and long-run causality tests between the healthcare sector and the other sector indexes during COVID-19-period. It contains the statistics of Causality in VECM.

Table 7 | Short- and Long-Run Causality in VECM. |
| --- | --- |
| Causality test | F-statistic |
| Test for Materials causes health | 2.0129** |
| Test for Materials long-run causing health | 6.6503** |
| Test for health causes Materials | 1.1020 |
| Test for health long-run causing Materials | 1.8370 |
| Test for Industrials causes health | 1.5944 |
| Test for Industrials long-run causing health | 6.6025** |
| Test for health causes Industrials | 0.8894 |
| Test for health long-run causing Industrials | 2.9237* |
| Test for communication services causes health | 0.6815 |
| Test for communication services long-run causing health | 0.0387 |
| Test for health causes communication services | 0.5054 |
| Test for health long-run causing communication services | 0.0053 |
| Test for Financial causes health care | 1.4605 |
| Test for Financial long-run causing health | 8.9605*** |
| Test for health causes Financial | 0.9352 |
| Test for health long-run causing Financial | 4.6994** |
| Test for consumer discretionary causes health | 1.8020* |
| Test for consumer discretionary long-run causing health | 9.6476*** |
| Test for health care index causes consumer discretionary | 0.9487 |
| Test for health care index long-run causing consumer discretionary index | 2.8839* |

Notes: The above table shows the results of causality tests between the health sector and the other sector indexes during COVID-19-period. It contains the statistics of Causality in VECM. Rejection of the null hypothesis of no Causality at ***, ** and * is denoted by 1%, 5% and 10% levels of significance, respectively.
4. Conclusions

This study explored sectoral index co-movements in the US healthcare index during the COVID-19 pandemic. Our findings demonstrate that the pandemic has had a significant impact on the cointegration of sector indexes. This investigation also shows that sector co-movements appeared during the COVID-19 period. In line with previous studies (Baker et al., 2020; Mazur et al., 2021), we argue that lockdown impacts the tendency of sector price indexes. This research area is relevant and significant, providing a better understanding of the relationships between different sector indexes. In line with Phylakitis and Xia (2009), we can conclude that identifying sectoral contagion during this pandemic has great importance for portfolio diversification. Our findings also have policy implications for regulators, investors, and other market stakeholders. With co-movement assessment tools, policymakers can design appropriate interventions to moderate risk from the co-movement of financial assets. Understanding the sectoral co-movement and timely healthcare policy decisions during a pandemic is also critical for investors, portfolio managers, policymakers, and other market participants, allowing stakeholders to be better prepared to adopt strategies for successfully limiting risks during future health crises.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.frl.2021.102295.

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