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COVID-19 social distancing and the US service sector: What do we learn?

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ABSTRACT

This study investigates the impact of COVID-19 social distancing on the US service sector. Results from four industry indexes (hotels, entertainment, restaurants and airlines) indicate that conditional correlations among index pairs exhibited substantial increases. Iterated Cumulative Sums of Squares (ICSS) tests in dynamic conditional correlations show that while the relationship between airlines and entertainment venues is unstable, restaurants and hotels demonstrate stable co-movement. Markov regime-switching regression analysis suggests the pandemic is affecting mainly the entertainment and airline industries, with gradual deterioration in the hotel industry, led by small-market-cap companies. However, we see no evidence of a negative impact on the restaurant industry from the pandemic in our analysis period. This may be related to Maslow's hierarchy of needs. Based on our results, we recommend employment of effective working capital and supply chain management methods in the service sector to streamline the operations of affected companies. In addition, all other sectors should utilize appropriate methods of risk measurement and should take 'Black Swans' into account to incorporate a more accurate probability of unexpected events.

1. Introduction

For thousands of years, humans have slowly transitioned from an agricultural to an information-based economy. Across the historical phases of economic development, the service sector is the most recently developed. Currently, most OECD countries have already transformed into predominantly service economies. The first transition occurred in the US in the middle of the twentieth century (Cheng, 2013). The driving force behind expansion of the service sector in developed countries stems from the cost advantages of emerging economies. Thanks to their lower manufacturing costs and product duplication capabilities, some developing countries are now among the most important manufacturing centers in the world. The competitive advantage of developing economies, such as China, pushes developed countries toward higher value-added and new high-technology products that incorporate knowledge management and investment in intangibles. Today, telecommunications, finance, and business services stand at the fore, given their substantially higher research and development (R&D) investment (Sheehan, 2006). Statistics bear out this transition (see Fig. 1). According to the BLS (2020a,b), the top four employment sectors in the US are education and health services, professional and business services, leisure and hospitality, and retail trade, respectively. Manufacturing takes fifth place, accounting for 9.9 % of total employment. Additionally, concurrent with globalization, the contribution of manufacturing to value-added GDP has declined

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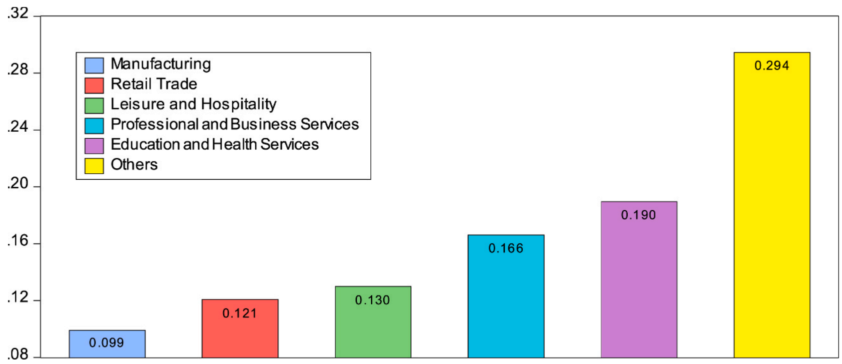

Fig. 1. Employment Rates in Different Sectors in the US.

significantly in recent years, from 26 % in 1947 to 16 % in 1997. By 2018, it had fallen further, to 11 %. However, this contribution stood at 30 % in China in 2018 (World Bank Report, 2020).

The size of the service sector renders it susceptible to potential risks, especially following the Global Financial Crisis (GFC) and the advent of the concept of 'too big to fail.' Substantially higher contributions to employment and GDP and its efficiency in fueling economic growth make the service sector a vulnerable piece of the US economy. This fact applies not only to the US but also to most OECD countries. The vital importance of the service sector in spurring economic growth forced all those countries to take measures against the recent pandemic. These actions were made necessary by the speed of contamination and the pandemic's influence on the service and manufacturing sectors, threatening the economic stability of many countries. As stated by Goodell (2020), the pandemic may cause economic havoc through its heavy economic costs. The lessons taken from such an experience will become vital in terms of risk management and policy implications. Below, we discuss what we have learned from the COVID-19 pandemic.

As in the Asian Crisis of 1997 and the GFC, this pandemic once again reveals that while the integration of financial markets provides some benefits, such as high liquidity and easy access to international funds in tranquil periods, it also intensifies the contagion effect in the face of economic turbulence and may cause the extent of risk to exceed the exposure limits of many economies. Although the causes and phases of the pandemic differ from the GFC, once again, aggressive financial support and monetary easing are required to boost customer spending, as in the GFC. For example, as reported by Bartik et al. (2020), the amount of aid necessary for small businesses to survive may reach $410 billion in the US alone. However, unlike the GFC, strong regulatory controls are not a remedy for financial market turbulence. Stay-at-home and social distancing practices have taught us to recalibrate our everyday lives, and such changes will directly affect business processes and operational modalities, especially in service sector businesses such as bars and restaurants, hotels, educational institutions, and airlines (Strong and Welburn, 2020). The pandemic demonstrates that diversification is critical, not only for portfolio managers but also for multinational corporations. Even during the pandemic, a proper diversification strategy can eliminate excessive exposure to a particular stand-alone asset, sector, or country.

Another lesson is the speed and effectiveness of the response in several countries depending on their independent policy decision-making or dependence on a geopolitical entity such as the EU. Despite common markets and common external borders, EU member nations remained uncoordinated in response to the pandemic. For example, due to uncertainties and domestic needs during the COVID-19 pandemic, EU countries were unable to act in solidarity, and failed to follow their non-discrimination principles and values, especially in the early stages of the pandemic. The pandemic has also drastically increased the presence of digital technology in our personal lives. Through acceleration of the digital transformation, remote work, e-learning, and even remote health services have become practicable. Considering its unpredictability and severe consequences, this pandemic can be regarded as a Black Swan; however, this Black Swan affects not only particular markets or economies, but the entire world. As discussed by Taleb (2007), Black Swans require us to update our risk measurement and risk management models and force us to allocate more space for unexpected events in the tails of probability distributions. This reality necessitates exclusion from our analysis of statistical models based on random walk or normal distribution, which allocate only thin tails for outliers. Another important lesson from the pandemic relates to supply chain management. The pandemic has shown that dependence on a particular supplier can jeopardize an entire business. Considering the role of China in the global economy, companies should create alternative sources of supply and update their inventory policies. This policy change means that diversification strategies also apply to various business processes. Although working capital management is essential even in tranquil periods, the pandemic highlights and emphasizes its importance. Forecasting future cash flows has become quite uncertain since the pandemic disrupted business operations, and forecasting models have begun to malfunction. This is why it is recommended that the cash conversion cycle during a pandemic or any turbulence event should be monitored carefully to prevent liquidity strain. Another measure is to increase the frequency of cash flow forecasting and provide up-to-date data from suppliers and customers. Additionally, the pandemic has taught us that mutually beneficial relationships can well serve both suppliers and customers given reduced access to external funds or a liquidity crunch in crisis periods.

There is a consensus that the current unprecedented crisis requires extraordinary economic measures. However, lockdowns, quarantines, and transportation restrictions have already distorted market equilibrium in supply and demand. Breakdowns in the supply chain and halts to production indicate that recovery will be prolonged in many economies. It is expected that sectors that require social interaction, such as travel, hospitality, entertainment, and tourism, will be most impacted, as the imposed measures curtail mobility and fuel health concerns (IMF, 2020). Under these circumstances, one possible outcome of the pandemic is extended social distancing practices. As discussed in Fernandez-Duque and Wifall (2007), with social distance practices in place, people's decision making relies on both rational and experiential factors. Thus, social distancing begins to play an essential role in people's economic activities, changing their attitudes and habits toward specific sectors. This change in behavior may be more visible in the service sector, because it requires close contact with customers. Accordingly, we examine the influence of COVID-19 on the US service sector. We study stock returns for four service sector industries: hotels, entertainment, restaurants, and airlines. As stated by Fama (1970), according to the Efficient Market Hypothesis, the current stock price should incorporate all available information about a firm. As per this proposition, we assume that investor expectations are already reflected in service sector firms' stock prices during the COVID-19 pandemic. This price reflection requires the correction of asset returns based on future expectations of investors. This approach allows us to gauge the extent of damage in the service sector due to the COVID-19 pandemic.

2. Literature review

The service sector in the US and other countries is extensively analyzed in the literature. For example, Mulder et al. (2014) examine 18 OECD countries' service sectors in the context of energy intensity. These authors conclude that a growing service sector brings about less energy intensity in these countries. June and Mahmood (2011) investigate job performance of employees in the service sector. According to their results, role ambiguity, competency, and person–job fit have statistically significant interactions. Cheng (2013) analyzes the elements essential to the development and growth of the service sector. This author defines these components as a specialized division of labor, innovation, and demand-induced mechanisms. Das and Raut (2014) discuss the importance of the service sector in terms of its contribution to the creation of human capital crucial to sustainable economic development. Buera and Kaboski (2012) emphasize the function of high-skilled labor in the asymmetrical growth of companies in the service sector. These authors empirically investigate how demand shifts toward output that is relatively skill-intensive. Jiménez-Zarco et al. (2011) examine the significance of market orientation in the tourism sector. Their results show that employment of information and communication technologies has dual direct and indirect effects on innovative services. Ebling and Janz (1999) analyze the German service sector in the context of export and innovation relationships. Their results demonstrate that export levels do not have a statistically significant effect on the innovation activities of German service companies. More specifically, studies on the influence of the service sector on economic growth present consistent results. Rudenko et al. (2015) state that small businesses in the service sector have made a significant contribution to the economic development of Russia. Castillo et al. (2014) study the explanatory power of the service sector on the growth of the Mexican economy. Their cointegration analysis suggests that GDP and secondary and tertiary sectors show a common trend. While Asian economies are generally considered export-oriented manufacturing centers, Park and Shin (2012) find empirical results that show a substantial contribution from the service sector to Asian economic growth. Lee and McKibbin (2014) also provide evidence from Asian economies. These authors state that productivity growth in the service sector yields sustainable economic development in Asian countries.

The impact of financial crises and social developments on the service sector is examined in several studies. Romao et al. (2016) investigate the impact of the GFC on tourism in Portugal's Algarve through Bayesian vector auto-regression analysis. Similarly, Dibeh et al. (2020) explore the influence of the Syrian Crisis on the tourism–growth nexus in Lebanon. According to their results, the Lebanese economy is quite resilient to political developments caused by the Syrian Crisis. Dwyer et al. (2006) discuss the influence of the Iraq War and SARS on the Australian economy. Fenichel (2013) compares various social distancing incentives. According to this author, social distancing is an effective strategy to stop the spread of diseases.

Studies examining the impact of the COVID-19 pandemic and social distancing measures are quite limited because this is a new phenomenon and there has been no pandemic on such a large scale in recent history. Nonetheless, new studies are emerging. Courtemanche et al. (2020) examine the impact of social distancing measures in the US. Their results show that government-imposed social distancing measures reduced COVID-19 cases by about 9.1 % after 16–20 days. Greenstone and Nigam (2020) introduce a method to gauge the impact of social distancing on the death toll from the pandemic. According to the findings, the implementation of moderate social distancing in March would save 1.7 million lives in the United States by October 1. Ahmed et al. (2018) conduct electronic searches of various databases and show that workplace social distancing reduced the overall number of influenza cases. Mongey et al. (2020) find that economic risk exposure is higher in workers in low-work-from-home or high-physical-proximity jobs during the pandemic. Tucker and Yu (2020) examine the pandemic's impact on US retail foot traffic utilizing visit data attained through cell-phone tracking. These authors find that dine-in restaurants suffered the greatest impact and the largest drop in revenues due to state-imposed bans. Nicola et al. (2020) discuss the socio-economic impacts of the pandemic on the world economy and state that the COVID-19 pandemic has created a Black Swan effect on the service sector because of social distancing, self-isolation, and lockdown precautions. These authors expect the greatest impact in hospitality, tourism, aviation, real estate, and housing. They also examine other dynamics through domestic violence and leisure activity. Ozili and Arun (2020) find that the healthcare sector may experience challenges as problems arise in the pharmaceutical supply chain. Further, these authors state that there may also develop financial difficulties in the healthcare sector. For instance, 150 hospitals in the US had to ask doctors and health personnel to leave or accept pay cuts during the pandemic. Shin and Kang (2020) expect the US hotel industry to lose 50 % of revenue because of the lowest recorded occupancy rate (38 %) since the Great Depression. Martinez Dy and Jayawarna (2020) investigate the effects of the pandemic on UK self-employed women and women-owned businesses. Their empirical analysis takes into account race, class, and gender data. Results indicate that precarity increases among marginalized entrepreneurs in the UK. Atkeson (2020) introduces a simple SIR model to examine the pandemic's spread by considering different population categories. This author investigates different scenarios regarding the staff and financial capacity of the healthcare system. Elavarasan et al. (2020) examine the shift in demand for electricity in the pandemic period. These authors state that residential, commercial, and industrial demand loads changed significantly due to the pandemic. To understand the economic effect of social distancing measures, Chetty et al. (2020) formed a publicly available database, updated daily, on consumer spending, unemployment rates, and business income. Results show a sharp decline in spending by high-income individuals due to health concerns and social distancing in March 2020 and a rise in unemployment statistics. Goodell and Huynh (2020) examine 15 industries to uncover the impact of the pandemic. Results demonstrate abnormal returns in several industries. For example, while medical and pharmaceutical industries show positive returns, constituents of the service sector, including restaurants, hotels and motels show negative abnormal returns. Regarding the pandemic's impact on financial markets, Ashraf (2020) analyzes stock markets in light of confirmed cases and death toll data from 64 countries. Results show that the pandemic's impact varies over time, though the biggest impact was in the outbreak's early days. Williams (2020) reports that undeclared workers and enterprises in the Western Balkans have faced difficult times during the COVID-19 pandemic as they have no access to short-term financing provided by government institutions. Baker et al. (2020a) generate three real-time, forward-looking instability measures: equity market volatility, news-based economic ambiguity, and subjective uncertainty. The authors employ these indexes to measure the economic ambiguity that has emerged during the pandemic. Results indicate that US real GDP contraction may be around 11 % by the end of 2020. Rupani et al. (2020) report that widespread flight cancellation and restricted transportation, along with lockdown measures implemented worldwide, have positively affected the natural environment. According to these authors, changes are evident in carbon emissions, air quality, and water pollution statistics. Bonaccorsi et al. (2020) analyze the economic impact of the pandemic on Italian citizens. Results reveal a more severe effect from the lockdown on municipalities with higher financial capacity and that the pandemic has caused a significantly negative effect on national and local government fiscal revenues. Cepoi (2020) employs COVID-19-related news data to uncover the pandemic's impact on stock markets. This author states that COVID-19 induces asymmetric dependencies with pandemic related news. As an alternative, the author recommends utilizing more reliable communication channels. Gunay (2020) utilizes four different time intervals to investigate the pandemic's impact on stock markets. DCC-GARCH and DCC-FIGARCH models demonstrate that contagion effects from China are more severe in the Turkish stock market than other countries analyzed. Cox et al. (2020) study the heterogeneous impacts of COVID-19 on household expenditures and savings in the US by employing bank account data; results show that the sharp decrease in the pandemic's early days is related to the shock effect rather than disruption to the labor market. Baker et al. (2020b) investigate stock market reaction to the COVID-19 pandemic. According to their results, since the beginning of the 21 st century, nothing has impacted the stock market more forcefully than COVID-19.

3. Methodology: Markov regime-switching regression

Given that the time series $\{y_t\}_{t=1}^{T}$ displays a Gaussian regime-switching process, the regime-switching regression model can be written as follows:

$$y_t = x_t^{'}\beta_{S_t} + \sigma_{S_t}\varepsilon_t,\ \varepsilon_t \sim i.i.d.\ N(0,1) \tag{1}$$

where y_t is scalar and x_t is a $(k \times 1)$ vector of independent variables. This equation may contain the lagged values of the dependent variable. $S_t = i$ is the state variable with $i = 1,\ 2, \ldots,\ N$ and evolves following a Markov chain. For a two-regime case, the transition probabilities of the state variable are as follows:

$$P(S_t = i \mid S_{t-1} = j, z_t) = P_{ij}(z_t) \tag{2}$$

The Markov chain evolves independent of all observations of those elements of x_t not included in z_t. The constrained transition probabilities of the state variable can be presented as follows:

$$S_t = \left\{ \begin{matrix} 1\ if\ \eta_t < (a_{S_{t-1}} + z_t b_{S_{t-1}}) \\ 2\ if\ \eta_t \geq (a_{S_{t-1}} + z_t b_{S_{t-1}}) \end{matrix} \right\} \tag{3}$$

We assume that the joint density function of ε_t and η_t is bivariate normal to model endogenous regime switching:

$$\begin{bmatrix} \varepsilon_t \\ \eta_t \end{bmatrix} \sim N(0,\ \Sigma),\ \Sigma = \begin{bmatrix} 1 & \rho \\ \rho & 1 \end{bmatrix} \tag{4}$$

where ε_t and η_t are uncorrelated (Kim et al., 2008).

4. Empirical analysis

We examine the extent of the damage from the COVID-19 pandemic in the US service sector. Lockdowns and quarantines across the country have affected several aspects of the economy, and the service sector appears most impacted. This is partly because of social distancing measures imposed by local governments. Currently, in many countries, restaurants and cafes are closed and entertainment activities are suspended. Broken supply chains are threatening the functioning of economic systems. To look more closely at the extent of exposure of the service sector, we examine the statistical relationship among industries and test the influence of the COVID-19 pandemic on each. To that end, we employ several statistical analyses: the Kapetanios m-break unit root analysis, the DCC-GARCH model, the Iterated Cumulative Sums of Squares (ICSS) test, and the Markov Regime-Switching Regression (MRSR) analysis. We conduct econometric analyses through MATLAB, Ox-Metrics, Gauss, and E-Views. We generate industry indexes by employing five

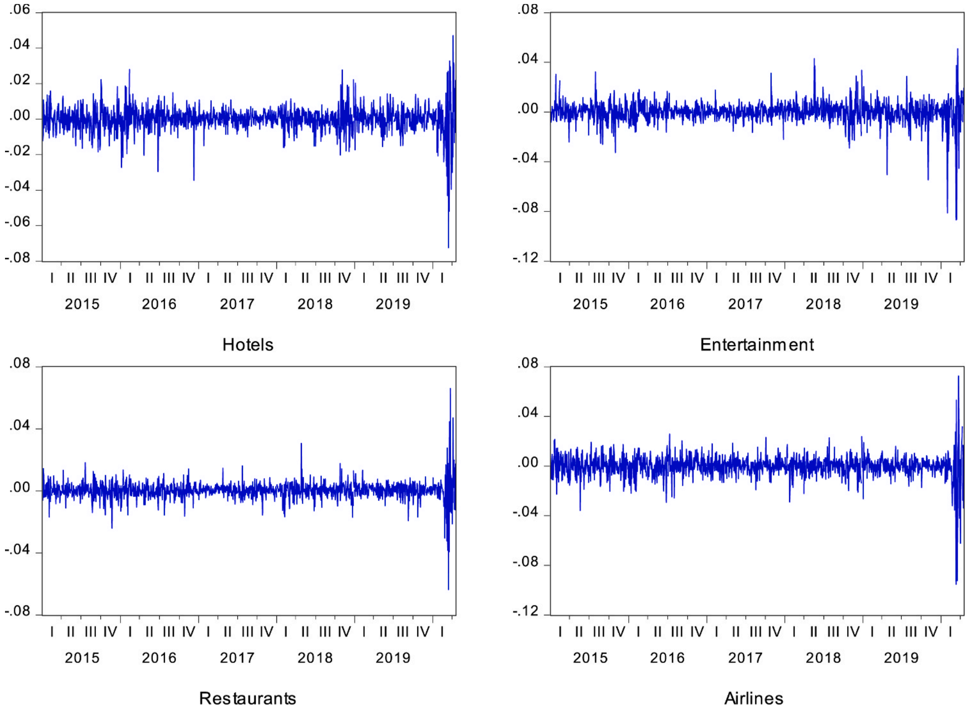

Fig. 2. Return Series of Industries (Weighted with Market Cap).

companies in each group. The company selection criterion is market capitalization. We use the five largest firms in terms of market cap. To generate index values, we utilize two weights: market-cap weights and equal weights for each firm. Equality in the weights allows us to avoid the size effects of the constituents. A list of the companies included in each industry index and their market caps are

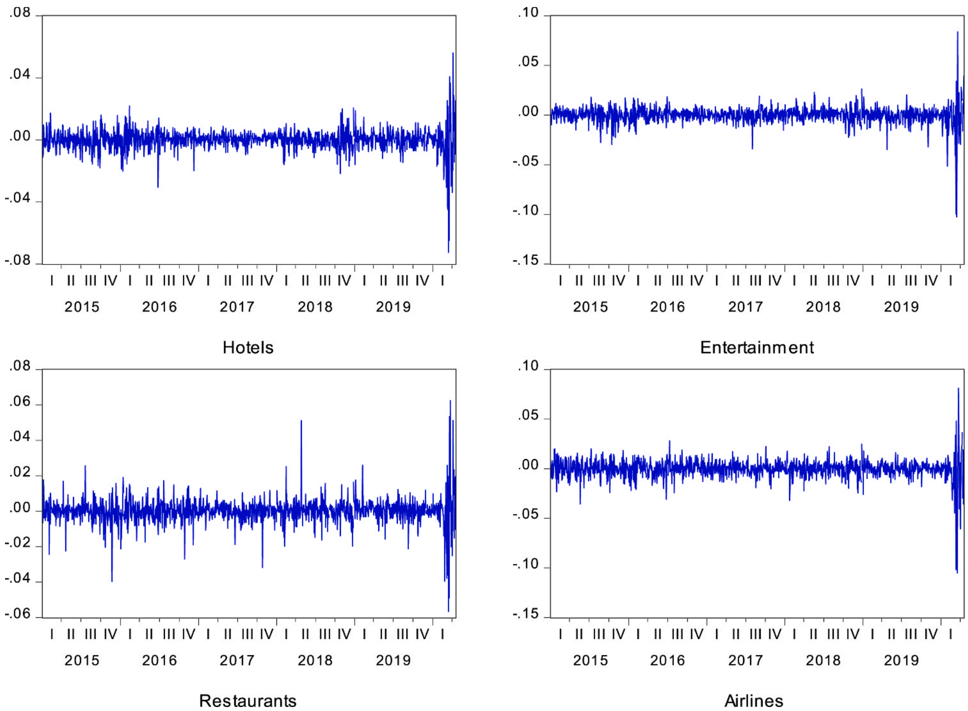

Fig. 3. Return Series of Industries (Evenly Weighted).

presented in Appendix A. As shown, each entity has a different market cap, and the values of the market caps display higher variability in the restaurant industry. The distribution of market caps might induce biased results among the industries. To overcome this problem, as mentioned above, we also create indexes with equal weights. The data utilized in the formation of indexes are the daily log-returns of stock prices for each company. Each time series covers January 2, 2005 to April 17, 2020 and was obtained from yahoo-finance.com. Returns of the created indexes are given in Figs. 2 and 3.

As shown, each index series exhibits similar fluctuation in terms of scale and timing. Despite still being in the midst of the pandemic, which may continue for some time, the variability of returns is high in the COVID-19 pandemic period and greater than in any other year. Figs. 2 and 3 show that the variability of returns declines in the hotel and entertainment industries when we use equal weights in the creation of the indexes. This may indicate that, in contrast to the restaurant and airline industries, in these two industries, the larger-market-cap companies have greater fluctuations in the return series. However, when we lower the weights of the larger-market-cap companies, the variability of returns in the restaurant and airline industries increases slightly. Unlike the first case, this shows that in these groups, smaller-market-cap companies exhibit larger changes in returns.

In Table 1, we present results for the descriptive statistics for each index series. According to the mean values of market-cap-weighted indexes, the highest average returns are observed in restaurants and entertainment, though both are very close to zero. When we change the weighting method, evenly weighted indexes indicate that hotels, restaurants, and entertainment firms show lower returns. It seems that lower-market-cap companies have lower average returns. Therefore, these constituents negatively affect the results, and mean returns decline. Regarding the variability of the return series, we can state that, in both groups of indexes, larger fluctuations occur in the returns of the airline and entertainment industries. While the variability of returns declines in hotels and entertainment firms along with the changes in weights, this variability rises for restaurants and airlines. These findings parallel our observations in the return graphs. The skewness and kurtosis test statistics indicate that all return series show departures from the Gaussian distribution. In both groups of indexes, hotels, entertainment, and airline companies display negative skewness, while restaurants show positive skewness. This means that the frequency of higher returns is greater in these three sectors. Kurtosis values indicate that all return series are leptokurtic. This finding is discussed in the following analysis. The significant the Jarque–Bera statistics also support these findings by rejecting the null hypothesis of the presence of a normal distribution for each variable.

Following analysis of the descriptive statistics, we execute unit root tests. Besides Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP), we implement a Kapetanios m-break unit root test. The unit root test is essential in financial time series analysis to check whether the data employed are stationary. As stated in Zivot and Wang (2003), the financial time series shows trending behavior that induces time-varying mean and variance. To remove the trend, in most cases, the first difference can make the data stationary.

Table 1
Descriptive Statistics.

	Weighted with Market Cap				Evenly Weighted			
	Hotels	Ent.	Rests	Airlines	Hotels	Ent.	Rests	Airlines
Mean	0.0001	0.0002	0.0002	−0.0002	0.0000	−0.0001	0.0001	−0.0002
Std. Dev.	0.0075	0.0090	0.0061	0.0092	0.0072	0.0087	0.0073	0.0096
Skewness	−1.1681	−2.0271	0.0307	−1.6592	−1.3552	−2.1265	0.0049	−1.8724
Kurtosis	16.160	24.160	30.470	24.830	22.670	39.190	19.350	29.300
J-B Statistic	9920	25762	41879	27056	21876	73701	14844	39152
p. value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Table 2
Unit Root Tests.

	Weighted with Market Cap				Evenly Weighted			
	Hotels	Ent.	Restaurants	Airlines	Hotels	Ent.	Restaurants	Airlines
Test Statistic	−24.3953	−24.4551	−25.0234	−34.8027	−23.1241	−23.1777	−24.4123	−34.8503
Break No	163 264 374 1002 1200	281 710 817 980 1108	124 257 463 797 1002	126 273 374 667 1197	162 263 374 1002 1200	159 279 666 817 980	123 259 785 1002 1111	125 273 374 667 1197
Break Dates	08.25.15 01.20.16 06.27.16 12.24.18 10.08.19	02.12.16 10.25.17 04.02.18 11.20.18 05.29.19	06.30.15 01.08.16 11.01.16 03.02.18 12.24.18	07.02.15 02.02.16 06.27.16 08.24.17 10.03.19	08.24.15 01.19.16 06.27.16 12.24.18 10.08.19	08.19.15 02.10.16 08.23.17 04.02.18 11.20.18	06.29.15 01.12.16 02.13.18 12.24.18 06.03.19	07.01.15 02.02.16 06.27.16 08.24.17 10.03.19
ADF	−16.5732	−11.5937	−23.5547	−33.9863	−14.0237	−13.1350	−22.4093	−34.0322
PP	−35.6750	−39.6925	−36.8946	−33.9071	−33.7924	−36.6589	−36.1562	−33.9689

Table 3
DCC-GARCH Model Estimation.

	Weighted with Market Cap		Evenly Weighted	
	Gaussian	Student-t	Gaussian	Student-t
R_{R_H}	0.3245***	0.3393***	0.3059***	0.3758***
	(−0.0504)	(−0.0398)	(0.0529)	(−0.0445)
R_{M_H}	0.3358***	0.4057***	0.4343***	0.4417***
	(−0.0543)	(−0.0367)	(−0.0388)	(−0.0345)
R_{A_H}	0.4481***	0.4490***	0.5092***	0.4869***
	(−0.0486)	(−0.0349)	(−0.0328)	(−0.0321)
R_{M_R}	0.2680***	0.2763***	0.2716***	0.2863***
	(−0.0456)	(−0.0429)	(−0.0450)	(−0.0427)
R_{A_R}	0.3050***	0.3191***	0.2784***	0.3272***
	(−0.0542)	(−0.0406)	(−0.0554)	(−0.0428)
R_{A_M}	0.3031***	0.3076***	0.3676***	0.3193***
	(−0.0478)	(−0.0376)	(−0.0357)	(−0.0376)
α	0.0097***	0.0147***	0.0189	0.0165***
	(−0.0031)	(−0.0039)	(−0.0137)	(−0.0057)
β	0.9727***	0.9607***	0.9206***	0.9545***
	(−0.0081)	(−0.0129)	(−0.0796)	(−0.0219)
df	–	4.9928***	–	5.2320***
		(−0.2503)		(0.2819)

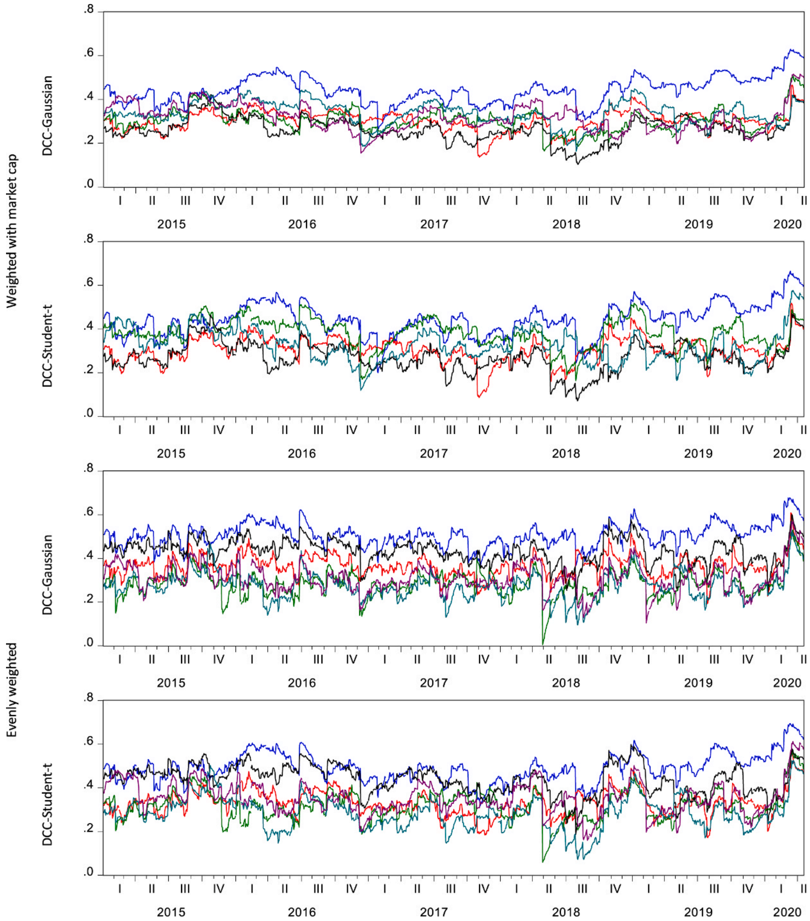

Fig. 4. Dynamic Conditional Correlations.

Non-stationary time series could bring about a spurious regression. Therefore, applying a unit root test to the data is vital for the soundness of the test statistics. Leybourne and Newbold (2003) and Kim et al. (2002) show that the presence of structural breaks could lead to an incorrect rejection of the null hypothesis for the unit root analysis. Kapetanios (2005) proposes a unit root test that is robust against structural breaks in the data. The model tests the null hypothesis of a unit root against the alternative hypothesis of an unspecified number of structural breaks. The test results indicate that the null hypothesis of each test is rejected at the 95 % confidence level, meaning all return series are stationary, I(0), in their level. In Table 2, we present the results of unit root tests.

Following the unit root test, we examine the dynamic conditional correlations of the return series of the indexes. In executing the analysis, we employ the DCC-GARCH model. By considering the departures from the Gaussian distribution seen in the descriptive statistics, along with the normal distribution, we utilize the Student's t-distribution in our estimations. The estimated dynamic conditional correlations are presented in Fig. 4. In Table 3, we provide results of the unconditional correlations to illustrate the interactions of the indexes. As this analysis is beyond the scope of this study, we do not elaborate on this discussion here. However, briefly, it can be stated that in most cases, the estimated unconditional correlation coefficients slightly increase in evenly weighted indexes. This result aligns with our theoretical expectations, because use of equal weights would smooth the idiosyncratic features of the variables.

To identify the turning points in the behavior of the dynamic conditional correlations, we execute the ICSS algorithm by employing the methodology of Sansó et al. (2020). We present the results in Table 4. However, because of space limitations, we include here only the break dates after June 2019. The complete findings are provided in the Appendix. As the results indicate, the highest number of breaks is found in the relationship between the airline and entertainment industries. The earliest break is observed in the correlations of the entertainment–hotel variables, and takes place on January 8, 2020. Other indexes draw our attention to two more dates. While restaurants–hotels, airlines–hotels, and airlines–restaurants show a break on February 24, 2020, entertainment–restaurants and airlines–entertainment indexes present a break on March 12, 2020.

Table 4
Detected Breaks in Dynamic Conditional Correlations of GARCH Models.

	No	Weighted with Market Cap						Evenly Weighted					
		R_{R_H}	R_{M_H}	R_{A_H}	R_{M_R}	R_{A_R}	R_{A_M}	R_{R_H}	R_{M_H}	R_{A_H}	R_{M_R}	R_{A_R}	R_{A_M}
DCCGARCH-n	1	24.02.20	12.08.19	05.08.19	13.06.19	24.02.20	09.10.19	14.08.19	07.01.20	19.07.19	03.12.19	05.02.20	08.01.20
	2	–	02.10.19	24.02.20	10.09.19	–	31.10.19	30.1219	–	11.10.19	25.02.20	24.02.20	21.01.20
	3	–	31.10.19	–	31.10.19	–	12.12.19	24.02.20	–	20.11.19	–	–	25.02.20
	4	–	08.01.20	–	12.03.20	–	08.01.20	–	–	21.01.20	–	–	–
	5	–	–	–	–	–	28.01.20	–	–	–	–	–	–
	6	–	–	–	–	–	12.03.20	–	–	–	–	–	–
DCCGARCH-t	1	24.02.20	25.07.19	01.08.19	17.06.19	05.02.20	25.07.19	14.08.19	5.08.19	23.07.19	04.06.19	14.06.18	12.08.19
	2	–	05.08.19	27.09.19	18.07.19	24.02.20	05.08.19	04.03.20	8.10.19	23.10.19	18.07.19	20.06.19	2.10.19
	3	–	02.10.19	27.01.20	11.03.20	–	09.09.19	–	8.01.20	20.11.19	05.08.19	05.08.19	9.10.19
	4	–	30.10.19	–	–	–	09.10.19	–	–	21.01.20	30.10.19	10.09.19	30.10.19
	5	–	08.01.20	–	–	–	01.11.19	–	–	–	09.12.19	04.11.19	3.12.19
	6	–	–	–	–	–	12.12.19	–	–	–	25.02.20	02.01.20	8.01.20
	7	–	–	–	–	–	08.01.20	–	–	–	–	31.01.20	24.01.20
	8	–	–	–	–	–	27.01.20	–	–	–	–	05.02.20	25.02.20
	9	–	–	–	–	–	12.03.20	–	–	–	–	24.02.20	–

Table 5
BDS Test results.

		Weighted with Market Cap				Evenly Weighted			
	e	$m = 3$	$m = 5$	$m = 7$	$m = 9$	$m = 3$	$m = 5$	$m = 7$	$m = 9$
	0.5	12.9168	16.8839	21.6543	29.325	10.6521	13.8818	19.4803	29.7002
Hotels	1	13.9586	16.5215	19.5187	23.2903	11.8678	14.1776	17.1507	20.7809
	1.5	16.1334	17.5767	18.9632	20.4915	13.0425	14.5271	15.9563	17.4756
	0.5	9.2498	9.8767	11.6486	12.9909	10.0161	11.224	13.4849	16.9265
Entertainment	1	10.3404	10.6985	11.3902	12.3032	11.6675	12.009	12.9308	13.9081
	1.5	10.954	10.7767	10.865	11.1391	12.7932	12.6116	12.7457	12.915
	0.5	8.0424	9.2368	10.7696	14.6735	9.1759	11.4166	14.5482	18.5956
Restaurant	1	9.7583	10.8273	12.044	13.7354	9.7464	11.3594	13.1659	15.0517
	1.5	11.2657	11.9655	12.7591	13.4511	9.4872	10.287	11.2926	11.8484
	0.5	5.1693	5.8558	6.3942	6.6217	5.8658	6.8441	7.3366	9.2323
Airlines	1	8.2197	8.6855	9.3515	10.1669	8.3812	9.0461	9.9323	11.1624
	1.5	12.7625	12.6241	12.7136	13.0694	12.3567	12.3216	12.4315	12.8995

Table 6
Markov Regime Switching Regression Analysis Results.

		Weighted with Market Cap				Evenly Weighted			
		Hotels	Ent.	Restaurant	Airlines	Hotels	Ent.	Restaurant	Airlines
R_1	DJ	1.4230***	0.7276***	1.2174***	1.0365***	−0.9393***	0.8716***	0.8435***	1.0535***
		(0.0444)	(0.0565)	(0.0636)	(0.0422)	(0.1085)	(0.0431)	(0.0286)	(0.0427)
	D	−0.0006	0.0026***	0.0054***	0.0029***	0.0067***	0.0028***	0.0002	0.0032***
		(0.0010)	(0.0010)	(0.0014)	(0.0009)	(0.0024)	(0.0009)	(0.0007)	(0.0009)
	c	0.0001	0.0005	0.0004	0.0000	0.0014	0.0000	0.0003	0.0000
		(0.0002)	(0.0003)	(0.0006)	(0.0003)	(0.0017)	(0.0003)	(0.0002)	(0.0003)
R_2	DJ	0.5659***	1.1172***	0.5175***	1.3282***	1.1067***	1.1601***	−0.9808***	1.4145***
		(0.0431)	(0.0777)	(0.0635)	(0.0828)	(0.0231)	(0.0641)	(0.1663)	(0.0776)
	D	0.0000	−0.0345***	−0.0004	−0.0341***	−0.0016***	−0.0348***	0.0136***	−0.0345***
		(0.0013)	(0.0028)	(0.0007)	(0.0025)	(0.0006)	(0.0025)	(0.0037)	(0.0022)
	c	−0.0001	−0.0010	0.0001	−0.0007	0.0000	−0.0004	−0.0212***	−0.0010
		(0.0003)	(0.0012)	(0.0002)	(0.0013)	(0.0001)	(0.0010)	(0.0018)	(0.0013)
	LL	5194.203	4685.749	5379.968	4842.108	5352.454	4838.877	4996.227	4802.794
	AIC	−7.785589	−7.022146	−8.064517	−7.256919	−8.023205	−7.252067	−7.488329	−7.197889
	HQ	−7.772437	−7.008993	−8.051364	−7.243767	−8.010052	−7.238914	−7.475176	−7.184736

Results of the Student's t-distribution are mostly consistent with these findings. When we change the weights of the indexes, we observe that evenly weighted indexes display more break dates. While previous models demonstrate a break on February 5 and February 24, 2020 in the airlines–restaurants relationship, the new model detects four turning points in this correlation series.

Note that, although the correlation coefficients demonstrate the strength and direction of a relationship, this analysis does not show which variable causes these breaks. However, what is clearly revealed from these results is the increasing number of breaks in evenly weighted indexes. The potential explanation could be the higher sensitivity of the lower-market-cap companies to the COVID-19 pandemic. It is clear that when we increase the weight of these companies in the configuration of the indexes, we observe more breaks than in the case of market-cap-weighted indexes. However, this finding does not hold for the entertainment–hotels relationship. In this segment, increased weight for the smaller-market-cap companies brings a declining number of breaks. To better relate this discussion to the COVID-19 pandemic, we examine its influence through MRSR analysis.

Hamilton (1989) states that financial time series show departures from linearity and might have regime shifts in their dynamic behaviors. To that end, the author introduces an algorithm to model turning points. Hamilton's algorithm, in fact, can be seen as an extension of the Neftci (1984) study on US unemployment. Sharp changes in the behavior of a financial time series are associated mainly with economic and social developments. A pandemic is a very good example of this. More specifically, recent suggestions by health authorities to increase social distancing may force people to change behavior and adapt to circumstances. Subsequently, changing consumer behavior due to strong external pressures may cause changes in the behavior of respective time series, consistent with previous findings. Considering the study of Hamilton (1989), first we examine the nonlinearity of the return series. To test whether the return series show a serial dependence and nonlinear structure, we employ the Brock, Dechert and Scheinkman (BDS) test of Brock et al. (1996). Considering the suggestion of Hsieh and LeBaron (1988), we utilize the following epsilon values, 0.5, 1, and 1.5, and select four different embedding dimensions. The BDS test results are presented in Table 5.

Since the results show that all test statistics are statistically significant at the 95 % confidence level, the null hypothesis of asset returns relevant to independent and identically distributed data generating process is rejected. The presence of nonlinearity in the variables demonstrates that the MRSR is an appropriate model for further investigation of COVID-19′s impact on the US service sector. Table 6 shows results from the MRSR model. In addition to the estimated coefficient of the models, we provide the regime-switching probabilities in Appendix F.

To form the MRSR model, we employ the index return series as dependent variables. As independent variables, we use the Dow Jones Industrial Average (DJIA) index returns and a dummy variable to gauge the impact of the pandemic. The dummy variable takes the value zero before January 2, 2020 and one up to the last observation. January 2, 2020 was selected as it was the first business day after the Chinese government's official notification to the World Health Organization regarding the outbreak on December 31, 2020. The DJIA index is considered an indicator for world stock markets in terms of risk appetite and tensions in financial markets. By employing DJIA index as an independent variable in our model, we are able to explain changes in the dependent variable that are highly linked to the general market trend.

The MRSR analysis characterizes the relationships of variables under two regimes or phases. Accordingly, our results are populated in two panels: regime one and regime two. In terms of theory, these regimes are generated by multiple equilibria in aggregate economic activity. Therefore, each might reflect the behavior of, for example, a contraction or expansion period. However, rather than the characterization of regimes, we focus on the coefficient of the dummy variable to reveal the impact of the COVID-19 pandemic. Compared to tranquil periods, the pandemic period might have higher volatility and, thus, lower predictability. The coefficients obtained for the dummy variable show consistent results under market-cap-weighted and evenly weighted models. Under each analysis, the entertainment and airline industries exhibit statistically significant coefficients for the dummy variable. The coefficients are around -0.03. The negative sign indicates that the COVID-19 pandemic has a negative influence on these two indexes.

Another interesting finding is the change in the coefficient of the hotel industry. When we evenly distribute the constituents inside each index, meaning that we lower the weight of larger-market-cap firms and increase the weight of smaller-market-cap firms, we see that the hotel industry has a negative coefficient. This may indicate that the gradual deterioration in the hotel industry begins in comparatively small firms' stock returns. We observe no negative influence in the restaurant industry caused by the pandemic. This result can be evaluated under the Maslow (1943, 1954) hierarchy of needs theory. Overall, the results depict that the COVID-19 pandemic has already affected the stock market, but the largest impact thus far is observed in the entertainment and airline industries. Our findings clearly support the sentiment that social distancing has impacted the service sector. Thus, especially for the most negatively impacted industries, we recommend corresponding actions regarding working capital and supply chain management. In addition, the COVID-19 pandemic shows that Black Swans, namely the high probability of unforeseen events, should be incorporated in risk measurement models. Conventional methods that utilize random walk or Gaussian distribution underestimate the probability of Black Swans by ignoring the fat tails in return distributions. Therefore, as discussed in Mandelbrot and Hudson (2007), managers who model risk and make forecasts should take into account the actual behavior of financial time series, which can be less predictable than the assumptions of conventional finance theory.

5. Conclusion

The COVID-19 pandemic has heavily impacted the most basic human interactions, due to drastic social distancing measures. While the policy responses have induced unprecedented contraction in particular portions of the service sector, such as hospitality, entertainment and transportation, the pandemic also created a growth opportunity for technology-intensive services. The contrasts in market reactions allows us to conduct an empirical investigation to uncover the actual impact of the pandemic on various segments of the service sector. New public information during the pandemic, from the number of new cases to vaccine news, pushed investors to update their portfolios accordingly. Thus, the reactions in asset prices are important signals regarding the negative or positive expectations in market trends. From this perspective, we examine four leading industries to show the impact of the pandemic on four areas of the service sector: airlines, restaurants, hotels, and entertainment.

We conduct empirical analyses on the returns of two indexes for each industry. To form the industry indexes, we utilize the stock price series of the five companies with the highest market caps in the corresponding industry. The indexes include market-cap weights and equal weights to control for the firm size effect. This configuration yields very interesting findings under almost all models. For example, descriptive statistics demonstrate that the variability of the return series of the hotel and entertainment industries decreases when we use equal weights. However, along with the equal weights, restaurants and airlines display higher fluctuations in returns. This indicates that lower-market-cap companies have higher volatility in returns in these two industries, while the opposite is observed in the case of hotels and entertainment. To observe the co-movements of industries, we also estimate conditional correlations of variable pairs for each industry. According to the results, with the pandemic, all index returns exhibit higher interconnectivity than any other period in the past. Following derivation of conditional correlations, we employ the ICSS test to detect breaks in the variance of these correlations. We have focused on the period of 2019-2020. The break dates obtained for the market-cap-weighted indexes show that the least number of breaks is observed in the correlation of the restaurant and hotel industries. However, the relationship between airlines and entertainment shows departures from stability, with six and nine breaks after July 2019, respectively. Similar results are observed under evenly weighted index returns.

To uncover the impact of the COVID-19 pandemic on the service sector, finally, we execute an MRSR analysis. In this method, we employ index returns as dependent variables. As independent variables, we use the DJIA index and a dummy variable representing the impact of the pandemic. The dummy variable was coded as 0 or 1, for before and after January 2, 2020, respectively. The results for the market-cap-weighted indexes demonstrate that the pandemic has had the strongest effect on two industries: entertainment and airlines. For both industries, the coefficient is around -0.03, which indicates a negative influence from the pandemic on returns for entertainment and airline stocks. The results for the equally weighted indexes demonstrate that the dummy variable in the hotel industry is significant, even though its coefficient is smaller than those in the entertainment and airline industries. This indicates that when we increase the weight of smaller-market-cap firms when forming the indexes, the hotel industry seems affected by the crisis, yet the deterioration seems to have begun in the stocks of relatively small companies. This gradual deterioration may increase along with the crisis and social distancing. However, this negative impact is not as bad as that observed in the entertainment and airline industries. Our results indicate no negative influence in stock returns of the restaurant industry. This may relate to the hierarchy of needs among the public. Considering our findings, we suggest that from working capital to supply chain management, firms in the service sector should take appropriate actions immediately. Risk management strategies should also be updated accordingly. Models based on conventional finance theory may underestimate the probability of Black Swans, since they incorporate the random walk and Gaussian distributions. However, the chance of unexpected events is greater than the predictions of these models, as already observed with Black Monday (1987), the GFC (2008), and the COVID-19 pandemic. This fact requires employment of appropriate approaches in risk measurement that consider the stylized facts of asset returns, such as volatility clustering, long memory, and fat tails.

Authorship information

Samet Gunay conceived, designed and executed the empirical analysis and interpreted the results. He also wrote the Introduction, Literature Review and Methodology. Bekir Emre Kurtulmuş contributed to Introduction and Literature Review sections.

Data sharing and data accessibility statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Declaration of Competing Interest

We declare that there is no conflict of interest, financial or otherwise that might influence the objectivity of our work.

Appendix A. Industries and Entities

	Symbol	Company Name	MarketCap
Hotels	LVS	Las Vegas Sands Corp.	35,422,000,000
	HLT	Hilton Worldwide Holdings Inc.	20,861,000,000
	IHG	InterContinental Hotels Group PLC	7,385,000,000
	MGM	MGM Resorts International	7,504,000,000
	H	Hyatt Hotels Corporation	5,631,000,000
Entertainment	WWE	World Wrestling Entertainment, Inc.	3,010,000,000
	CNK	Cinemark Holdings,Inc.	1,340,000,000
	MCS	The Marcus Corporation	415,000,000
	EROS	Eros International PLC	270,000,000
	AMC	AMC Entertainment Holdings, Inc.	251,000,000
Restaurants	MCD	McDonald's Corporation	132,000,000,000
	YUM	Yum! Brands, Inc.	23,400,000,000
	CMG	Chipotle Mexican Grill, Inc.	21,400,000,000
	QSR	Restaurant Brands International Inc.	12,500,000,000
	DRI	Darden Restaurants, Inc.	7,100,000,000
Airlines	LUV	Southwest Airlines Co.	15,869,000,000
	DAL	Delta Air Lines, Inc.	15,535,000,000
	UAL	United Airlines Holdings, Inc.	7,190,000,000
	AAL	American Airlines Group Inc.	4,930,000,000
	ALK	Alaska Air Group, Inc.	3,669,000,000

Appendix B. Detected Breaks in Dynamic Conditional Correlations of MVGARCH-n Model*

No	R_{R_H}	R_{M_H}	R_{A_H}	R_{M_R}	R_{A_R}	R_{A_M}
1	2.01.2015	2.01.2015	2.01.2015	2.01.2015	2.01.2015	2.01.2015
2	20.05.2015	8.06.2015	4.02.2015	21.08.2015	25.02.2015	27.01.2015
3	29.06.2015	29.06.2015	21.08.2015	20.11.2015	29.04.2015	29.10.2015
4	20.05.2016	4.08.2015	12.10.2015	17.03.2016	29.06.2015	13.01.2016
5	24.06.2016	1.09.2015	9.11.2015	2.05.2016	21.08.2015	22.04.2016
6	9.09.2016	24.06.2016	13.01.2016	24.06.2016	20.11.2015	9.09.2016
7	2.11.2016	23.08.2016	26.09.2016	19.07.2016	17.03.2016	8.11.2016
8	24.01.2017	8.12.2016	8.12.2016	10.11.2016	27.05.2016	7.12.2016
9	20.04.2017	4.01.2017	26.01.2017	25.07.2017	24.06.2016	9.02.2017
10	8.02.2018	10.03.2017	23.03.2017	15.11.2017	9.09.2016	17.05.2017
11	24.02.2020	21.03.2017	2.05.2017	17.05.2018	17.02.2017	18.07.2017
12	–	17.05.2017	17.05.2017	25.09.2018	20.06.2017	17.08.2017
13	–	19.07.2017	6.07.2017	28.11.2018	26.07.2017	3.10.2017
14	–	27.09.2017	17.08.2017	25.04.2019	3.01.2018	26.10.2017
15	–	12.10.2017	3.10.2017	13.06.2019	26.04.2018	5.12.2017
16	–	5.02.2018	5.02.2018	10.09.2019	7.11.2018	23.02.2018
17	–	17.05.2018	26.04.2018	31.10.2019	24.02.2020	17.05.2018
18	–	2.10.2018	26.07.2018	12.03.2020	–	26.07.2018
19	–	19.11.2018	10.10.2018	–	–	24.10.2018
20	–	15.02.2019	26.12.2018	–	–	24.12.2018
21	–	22.03.2019	20.02.2019	–	–	25.02.2019
22	–	12.08.2019	5.08.2019	–	–	27.03.2019
23	–	2.10.2019	24.02.2020	–	–	17.04.2019
24	–	31.10.2019	–	–	–	9.10.2019
25	–	8.01.2020	–	–	–	31.10.2019
26	–	–	–	–	–	12.12.2019
27	–	–	–	–	–	8.01.2020
28	–	–	–	–	–	28.01.2020
29	–	–	–	–	–	12.03.2020

*For the index weighted with market cap.

Appendix C. Detected Breaks in Dynamic Conditional Correlations of MVGARCH-t Model*

No	R_{R_H}	R_{M_H}	R_{A_H}	R_{M_R}	R_{A_R}	R_{A_M}
1	2.01.2015	2.01.2015	2.01.2015	2.01.2015	2.01.2015	2.01.2015
2	29.06.2015	28.01.2015	4.02.2015	21.08.2015	29.04.2015	27.01.2015
3	22.07.2015	8.06.2015	9.10.2015	24.11.2015	29.06.2015	29.10.2015
4	24.08.2015	1.09.2015	9.11.2015	29.04.2016	23.07.2015	7.01.2016
5	20.10.2015	7.03.2016	4.01.2016	24.06.2016	21.08.2015	22.04.2016
6	21.04.2016	24.06.2016	21.07.2016	19.07.2016	2.11.2015	3.05.2016
7	24.06.2016	18.08.2016	3.10.2016	9.11.2016	4.03.2016	16.06.2016
8	9.09.2016	8.11.2016	2.12.2016	24.07.2017	31.05.2016	21.07.2016
9	2.11.2016	8.12.2016	26.01.2017	21.08.2017	24.06.2016	9.09.2016
10	18.01.2017	4.01.2017	15.02.2017	28.11.2017	9.09.2016	28.10.2016
11	28.03.2017	16.02.2017	28.03.2017	30.01.2018	15.02.2017	20.12.2016
12	17.08.2017	1.06.2017	20.04.2017	17.05.2018	19.06.2017	9.02.2017
13	27.09.2017	19.07.2017	18.07.2017	1.10.2018	25.07.2017	12.07.2017
14	9.11.2017	27.10.2017	17.08.2017	17.06.2019	3.01.2018	17.08.2017
15	5.02.2018	2.02.2018	3.10.2017	18.07.2019	26.04.2018	3.10.2017
16	24.02.2020	1.05.2018	21.11.2017	11.03.2020	29.05.2018	26.10.2017
17		27.06.2018	8.02.2018	–	30.10.2018	29.11.2017
18	–	15.08.2018	26.03.2018	–	5.02.2020	12.02.2018
19	–	21.12.2018	26.04.2018	–	24.02.2020	17.05.2018
20	–	7.02.2019	26.07.2018	–		26.07.2018
21	–	22.03.2019	24.09.2018	–	–	20.08.2018
22	–	26.04.2019	19.11.2018	–	–	24.09.2018
23	–	17.05.2019	26.12.2018	–	–	21.12.2018
24	–	25.07.2019	14.02.2019	–	–	20.02.2019
25	–	5.08.2019	1.08.2019	–	–	13.05.2019
26	–	2.10.2019	27.09.2019	–	–	25.07.2019
27	–	30.10.2019	27.01.2020	–	–	5.08.2019
28	–	8.01.2020		–	–	9.09.2019
29	–		–	–	–	9.10.2019
30	–	–	–	–	–	1.11.2019
31	–	–	–	–	–	12.12.2019
32	–	–	–	–	–	8.01.2020
33	–	–	–	–	–	27.01.2020
34	–	–	–	–	–	12.03.2020

*For the index weighted with market cap.

Appendix D. Detected Breaks in Dynamic Conditional Correlations of MVGARCH-n Model*

No	R_{R_H}	R_{M_H}	R_{A_H}	R_{M_R}	R_{A_R}	R_{A_M}
1	2.01.2015	2.01.2015	2.01.2015	2.01.2015	2.01.2015	2.01.2015
2	5.05.2015	29.06.2015	4.02.2015	20.08.2015	4.02.2015	20.01.2015
3	29.06.2015	13.04.2016	6.03.2015	20.11.2015	6.03.2015	11.08.2015
4	22.07.2015	24.06.2016	20.05.2015	4.01.2016	10.04.2015	13.10.2016
5	24.08.2015	26.07.2016	8.06.2015	24.02.2016	29.04.2015	7.11.2016
6	12.10.2015	9.09.2016	3.08.2015	18.07.2016	29.06.2015	8.01.2020
7	4.01.2016	19.10.2016	20.08.2015	26.09.2016	20.07.2015	21.01.2020
8	14.07.2016	8.12.2016	2.11.2015	6.12.2016	5.02.2016	25.02.2020
9	6.12.2016	5.01.2017	13.01.2016	17.01.2017	7.06.2016	–
10	12.01.2017	18.09.2017	20.07.2016	21.03.2017	6.12.2016	–
11	23.03.2018	8.12.2017	30.08.2016	17.04.2017	10.01.2017	–
12	13.05.2019	17.05.2018	9.09.2016	20.06.2017	19.10.2017	–
13	14.08.2019	13.08.2018	22.09.2016	2.08.2017	26.04.2018	–
14	30.12.2019	2.04.2019	9.05.2018	28.08.2017	16.05.2018	–
15	24.02.2020	25.04.2019	7.06.2018	18.09.2017	25.06.2018	–
16		14.05.2019	26.07.2018	26.10.2017	20.12.2018	–
17	–	7.01.2020	24.09.2018	28.11.2017	14.01.2019	–
18	–		20.03.2019	3.01.2018	25.04.2019	–
19	–	–	1.05.2019	17.01.2018	5.02.2020	–
20	–	–	13.05.2019	2.04.2018	24.02.2020	–
21	–	–	19.07.2019	22.01.2019		–
22	–	–	11.10.2019	11.02.2019	–	–
23	–	–	20.11.2019	19.03.2019	–	–
24	–	–	21.01.2020	3.12.2019	–	–
25	–	–	–	25.02.2020	–	–

*For the index evenly weighted.

Appendix E. Detected Breaks in Dynamic Conditional Correlations of MVGARCH-t Model*

No	R_{R_H}	R_{M_H}	R_{A_H}	R_{M_R}	R_{A_R}	R_{A_M}
1	2.01.2015	2.01.2015	2.01.2015	2.01.2015	2.01.2015	2.01.2015
2	5.05.2015	10.03.2015	4.02.2015	22.01.2015	4.02.2015	20.01.2015
3	29.06.2015	24.08.2015	25.03.2015	20.03.2015	10.03.2015	10.03.2015
4	24.08.2015	9.11.2015	20.05.2015	21.08.2015	10.04.2015	20.05.2015
5	20.10.2015	11.12.2015	8.06.2015	20.11.2015	1.05.2015	19.06.2015
6	4.01.2016	7.03.2016	29.06.2015	4.01.2016	29.06.2015	24.08.2015
7	9.09.2016	10.05.2016	3.08.2015	28.09.2016	24.07.2015	13.10.2016
8	10.11.2016	17.01.2017	20.08.2015	6.12.2016	21.08.2015	22.12.2016
9	6.12.2016	2.10.2017	21.01.2016	25.04.2017	14.10.2015	12.07.2017
10	18.01.2017	2.02.2018	27.07.2016	20.06.2017	5.02.2016	10.08.2017
11	10.08.2017	17.05.2018	22.09.2016	25.10.2017	2.06.2016	19.10.2017
12	21.12.2017	27.06.2018	4.11.2016	22.12.2017	8.07.2016	18.12.2017
13	23.03.2018	15.08.2018	21.11.2016	19.01.2018	26.07.2016	17.05.2018
14	1.06.2018	5.08.2019	26.01.2017	2.04.2018	7.09.2016	12.08.2019
15	31.07.2018	8.10.2019	13.02.2017	28.06.2018	6.12.2016	2.10.2019
16	10.10.2018	8.01.2020	9.05.2017	10.10.2018	10.01.2017	9.10.2019
17	20.12.2018	–	25.05.2017	24.10.2018	23.08.2017	30.10.2019
18	23.05.2019	–	5.07.2017	19.12.2018	26.04.2018	3.12.2019
19	14.08.2019	–	17.08.2017	11.02.2019	14.06.2018	8.01.2020
20	4.03.2020	–	3.10.2017	12.03.2019	20.06.2019	24.01.2020
21	–	–	21.11.2017	25.04.2019	5.08.2019	25.02.2020
22	–	–	8.02.2018	4.06.2019	10.09.2019	–
23	–	–	11.06.2018	18.07.2019	4.11.2019	–
24	–	–	26.07.2018	5.08.2019	2.01.2020	–
25	–	–	26.09.2018	30.10.2019	31.01.2020	–
26	–	–	26.12.2018	9.12.2019	5.02.2020	–
27	–	–	24.01.2019	25.02.2020	24.02.2020	–
28	–	–	20.03.2019	–	–	–
29	–	–	1.05.2019	–	–	–
30	–	–	13.05.2019	–	–	–
31	–	–	23.07.2019	–	–	–
32	–	–	23.10.2019	–	–	–
33	–	–	20.11.2019	–	–	–
34	–	–	21.01.2020	–	–	–

*For the index evenly weighted.

Appendix F. Regime Transition Probabilities

		Regimes	1	2
Weighted with Market Cap	Hotels	1	0.4992	0.5008
		2	0.7195	0.2805
	Entertainment	1	0.8261	0.1739
		2	0.7459	0.2541
	Restaurant	1	0.2972	0.7028
		2	0.1317	0.8683
	Airlines	1	0.8742	0.1258
		2	0.6198	0.3802
Evenly Weighted	Hotels	1	0.8225	0.1775
		2	0.5560	0.4440
	Entertainment	1	0.8578	0.1422
		2	0.8279	0.1721
	Restaurant	1	0.9868	0.0132
		2	0.9461	0.0539
	Airlines	1	0.8627	0.1373
		2	0.6564	0.3436

References

Ahmed, F., Zviedrite, N., Uzicanin, A., 2018. Effectiveness of workplace social distancing measures in reducing influenza transmission: a systematic review. BMC Public Health 18 (1), 518.

Ashraf, B.N., 2020. Stock markets' reaction to COVID-19: cases or fatalities? Res. Int. Bus. Financ. 54, 101249.

Atkeson, A., 2020. What Will Be the Economic Impact of covid-19 in the Us? Rough Estimates of Disease Scenarios (No. w26867). National Bureau of Economic Research.

Baker, S.R., Bloom, N., Davis, S.J., Terry, S.J., 2020a. Covid-induced Economic Uncertainty (No. w26983). National Bureau of Economic Research.

Baker, S.R., Bloom, N., Davis, S.J., Kost, K., Sammon, M., Viratyosin, T., 2020b. The unprecedented stock market reaction to COVID-19. The Review of Asset Pricing Studies. https://doi.org/10.1093/rapstu/raaa008 raaa008.

Bartik, A.W., Bertrand, M., Cullen, Z., Glaeser, E.L., Luca, M., Stanton, C., 2020. The impact of COVID-19 on small business outcomes and expectations. Proc. Natl. Acad. Sci. 117 (30), 17656–17666.

BLS (2020a) https://www.bls.gov/opub/mlr/2016/article/current-employment-statistics-survey-100-years-of-employment-hours-and-earnings.htm.

BLS (2020b) https://www.bls.gov/charts/employment-situation/employment-levels-by-industry.htm.

Bonaccorsi, G., Pierri, F., Cinelli, M., Flori, A., Galeazzi, A., Porcelli, F., et al., 2020. Economic and social consequences of human mobility restrictions under COVID-19. Proc. Natl. Acad. Sci. 117 (27), 15530–15535.

Brock, W.A., Dechert, W.D., Scheinkman, J.A., LeBaron, B., 1996. A test for independence based on the correlation dimension. Econ. Rev. 15 (3), 197–235.

Buera, F.J., Kaboski, J.P., 2012. The rise of the service economy. Am. Econ. Rev. 102 (6), 2540–2569.

Castillo, R., Flores, C., Rodríguez, M., 2014. The relative importance of the service sector in the Mexican economy: a time series analysis. Lect. de Econ. (80), 133–151.

Cepoi, C.O., 2020. Asymmetric dependence between stock market returns and news during COVID19 financial turmoil. Financ. Res. Lett.

Cheng, D., 2013. The development of the service industry in the modern economy: mechanisms and implications for China. China Financ. Econ. Rev. 1 (1), 3.

Chetty, R., Friedman, J.N., Hendren, N., Stepner, M., 2020. How Did COVID-19 and Stabilization Policies Affect Spending and Employment? A New Real-time Economic Tracker Based on Private Sector Data (No. w27431). National Bureau of Economic Research.

Courtemanche, C., Garuccio, J., Le, A., Pinkston, J., Yelowitz, A., 2020. Strong social distancing measures in the United States reduced the COVID-19 growth rate: study evaluates the impact of social distancing measures on the growth rate of confirmed COVID-19 cases across the United States. Health Aff. 10–1377.

Cox, N., Ganong, P., Noel, P., Vavra, J., Wong, A., Farrell, D., Greig, F., 2020. Initial Impacts of the Pandemic on Consumer Behavior: Evidence from Linked Income, Spending, and Savings Data. University of Chicago, Becker Friedman Institute for Economics Working Paper (2020-82).

Das, L., Raut, R., 2014. Impact of changes in service sector in India in shaping the future of business & society. Procedia Econ. Financ. 11, 795–803.

Dibeh, G., Fakih, A., Marrouch, W., 2020. Tourism–growth nexus under duress: lebanon during the Syrian crisis. Tour. Econ. 26 (3), 353–370.

Dwyer, L., Forsyth, P., Spurr, R., Van Ho, T., 2006. Economic effects of the world tourism crisis on Australia. Tour. Econ. 12 (2), 171–186.

Ebling, G., Janz, N., 1999. Export and innovation activities in the German service sector: empirical evidence at the firm level. Working Paper.

Elavarasan, R.M., Shafiullah, G.M., Kannadasan, R., Mudgal, V., Arif, M.T., Jamal, T., et al., 2020. COVID-19: impact analysis and recommendations for power sector operation. Appl. Energy, 115739.

Fama, E.F., 1970. Efficient capital markets: a review of theory and empirical work. J. Finance 25 (2), 383–417.

Fenichel, E.P., 2013. Economic considerations for social distancing and behavioral based policies during an epidemic. J. Health Econ. 32 (2), 440–451.

Fernandez-Duque, D., Wifall, T., 2007. Actor/observer asymmetry in risky decision making. Judgm. Decis. Mak. 2 (1), 1–8.

Goodell, J.W., 2020. COVID-19 and finance: agendas for future research. Financ. Res. Lett., 101512 https://doi.org/10.1016/j.frl.2020.101512.

Goodell, J.W., Huynh, T.L.D., 2020. Did congress trade ahead? considering the reaction of US industries to COVID-19. Financ. Res. Lett., 101578 https://doi.org/10.1016/j.frl.2020.101578.

Greenstone, M., Nigam, V., 2020. Does Social Distancing Matter? University of Chicago, Becker Friedman Institute for Economics Working Paper (2020-26).

Gunay, S., 2020. A New Form of Financial Contagion: COVID-19 and Stock Market Responses. Available at SSRN 3584243.

Hamilton, J.D., 1989. A new approach to the economic analysis of nonstationary time series and the business cycle. Econometrica: J. Econometric Soc. 357–384.

Hsieh, D., LeBaron, B., 1988. Small Sample Properties of the BDS Statistic, I. Graduate School of Business. University of Chicago.

IMF (2020) https://www.imf.org/en/Publications/WEO/Issues/2020/04/14/weo-april-2020.

Jiménez-Zarco, A.I., Martínez-Ruiz, M.P., Izquierdo-Yusta, A., 2011. Key service innovation drivers in the tourism sector: empirical evidence and managerial implications. Serv. Bus. 5 (4), 339.

June, S., Mahmood, R., 2011. The relationship between role ambiguity, competency and person-job fit with the job performance of employees in the service sector SMEs in Malaysia. Bus. Manage. Dyn. 1 (2), 79–98.

Kapetanios, G., 2005. Unit-root testing against the alternative hypothesis of up to m structural breaks. J. Time Ser. Anal. 26 (1), 123–133.

Kim, T.H., Leybourne, S., Newbold, P., 2002. Unit root tests with a break in innovation variance. J. Econom. 109 (2), 365–387.

Kim, C.J., Piger, J., Startz, R., 2008. Estimation of Markov regime-switching regression models with endogenous switching. J. Econom. 143 (2), 263–273.

Lee, J.W., McKibbin, W.J., 2014. Service Sector Productivity and Economic Growth in Asia. Working Paper.

Leybourne, S.J., Newbold, P., 2003. Spurious rejections by cointegration tests induced by structural breaks. Appl. Econ. 35 (9), 1117–1121.

Mandelbrot, B., Hudson, R.L., 2007. The Misbehavior of Markets: a Fractal View of Financial Turbulence. Basic Books.

Martinez Dy, A., Jayawarna, D., 2020. Bios, mythoi and women entrepreneurs: A Wynterian analysis of the intersectional impacts of the COVID-19 pandemic on self-employed women and women-owned businesses. Int. Small Bus. J. 38 (5), 391–403.

Maslow, A.H., 1943. A theory of human motivation. Psychol. Rev. 50 (4), 370–396.

Maslow, A.H., 1954. Motivation and Personality. Harper and Row, New York.

Mongey, S., Pilossoph, L., Weinberg, A., 2020. Which Workers Bear the Burden of Social Distancing Policies? (No. w27085). National Bureau of Economic Research.

Mulder, P., De Groot, H.L., Pfeiffer, B., 2014. Dynamics and determinants of energy intensity in the service sector: a cross-country analysis, 1980–2005. Ecol. Econ. 100, 1–15.

Neftci, S.N., 1984. Are economic time series asymmetric over the business cycle? J. Polit. Econ. 92 (2), 307–328.

Nicola, M., Alsafi, Z., Sohrabi, C., Kerwan, A., Al-Jabir, A., Losifidis, C., et al., 2020. The socio-economic implications of the coronavirus pandemic (COVID-19): a review. Int. J. surgery (London, England) 78, 185–193.

Ozili, P.K., Arun, T., 2020. Spillover of COVID-19: Impact on the Global Economy. Available at SSRN 3562570.

Park, D., Shin, K., 2012. The Service Sector in Asia: Is It an Engine of Growth? Asian Development Bank Economics Working Paper Series (322).

Romao, J., Guerreiro, J., Rodrigues, P.M., 2016. Tourism growth and regional resilience: the 'beach disease'and the consequences of the global crisis of 2007. Tour. Econ. 22 (4), 699–714.

Rudenko, L., Zaitseva, N., Larionova, A., Chudnovskiy, A., Vinogradova, M., 2015. Socio-Economic role of service-sector small business in sustainable development of the Russian economy. European Res. Studies 18 (3), 223.

Rupani, P.F., Nilashi, M., Abumalloh, R.A., et al., 2020. Coronavirus pandemic (COVID-19) and its natural environmental impacts. Int. J. Environ. Sci. Technol. https://doi.org/10.1007/s13762-020-02910.

Sansó, A., Carrion, J.L., Aragó, V., 2020. Testing for changes in the unconditional variance of financial time series. Revista de Econ. Financiera 4, 32–52, 2004.

Sheehan, J., 2006. Understanding service sector innovation. Commun. ACM 49 (7), 42–47.

Shin, H., Kang, J., 2020. Reducing perceived health risk to attract hotel customers in the COVID-19 pandemic era: focused on technology innovation for social distancing and cleanliness. Int. J. Hosp. Manag. 91, 102664.

Strong, A., Welburn, J.W., 2020. An Estimation of the Economic Costs of Social-Distancing Policies. RR-A173-1. Randa Corporation.

Taleb, N.N., 2007. The Black Swan: The Impact of the Highly Improbable, 2. Random house.

Tucker, C.E., Yu, S., 2020. The Early Effects of Coronavirus-related Social Distancing Restrictions on Brands. Available at SSRN 3566612.

Williams, Colin, COVID-19 and Undeclared Work: Impacts, Challenges and Policy Responses (August 10, 2020). Williams, C.C. (2020) COVID-19 and Undeclared Work: impacts, challenges and policy responses. Regional Cooperation Council, Sarajevo., Available at SSRN: https://ssrn.com/abstract=3672437.
World Bank Report (2020) https://data.worldbank.org/indicator/NV.IND.MANF.ZS?locations=US.
Zivot, E., Wang, J., 2003. Rolling analysis of time series. In Modeling Financial Time Series with S-Plus®. Springer, New York, NY.