# COVID-19, stock market and sectoral contagion in US: a time-frequency analysis

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ABSTRACT

We assess the conditional relationship in the time-frequency domain between the return on S&P 500 and the cases or deaths by COVID-19 in Hubei, China, countries with record deaths and the world, for the period from January 29 to June 30, 2020. Methodologically, we follow Aguiar-Conraria et al. (2018), by using partial coherencies, phase-difference diagrams, and gains. We also perform a parametric test for Granger-causality in quantiles developed by Troster (2018). We find that short-term cycles of deaths in Italy in the first days of March and soon afterwards, cycles of deaths in the world are able to lead out-of-phase US stock market. We find that low frequency cycles of the US market index in the first half of April are useful to anticipate in an anti-phasic way the cycles of deaths in the US. We also explore sectoral contagion, based on dissimilarities, Granger causality and partial coherencies between S&P sector indices. Our findings, such as the strategic role of the energy sector, which first reacted to the pandemic, or the evidence about predictability of the Telecom cycles, are useful to tell the history of the pass-through of this recent health crises across the sectors of the US economy.

## 1. Introduction

The novel coronavirus outbreak, which began in Wuhan, China, in December, has expanded to touch every corner of the world, and on March 11, 2020, the World Health Organization defined it to be of a global nature. This pandemic scenario is neither new nor rare, so that there are similarities between the current moment and other ones of humanity, in which diseases spread throughout the globe and caused havoc.

The smallpox plagued mankind for more than 3,000 years. The bubonic plague caused the Black Death, which devastated Europe in the 14th century, killing more than 75 million people. The Cholera epidemic, in 1817, killed hundreds of thousands of people. Between 40 and 50 million people are believed to have died in the Spanish flu pandemic of 1918. More recently, H1N1 – the first pandemic caused in the 21st century.

Observing COVID-19 numbers by the end of June 2020, there are 10.3 million cases of coronavirus and 500 thousand deaths worldwide. It is worrying to note that the US has 4% of the world's population but 25% of its COVID cases. As a result of 127 thousand deaths in the US, the restriction was extended in several cities in California and Texas, while the state of Arizona announced the closure of bars, restaurants, and other leisure establishments for 30 days, among other public policy.

Regarding the impacts, the hesitation and contradiction in the measures adopted by policy makers in most countries severely affected by the virus, and the specific issues of this pandemic – insufficient hospital capacity, social distancing, a possible second wave and the uncertainty caused in the productive sectors – made its impact on the economy quickly devastating and whose consequences are difficult to predict. Even worse, some of the impacts are not on the real side of the economy. In Conlon, Corbet and McGee (2020), one can see the impacts on cryptocurrency markets, while according to Leslie and Wilson (2020), due to the

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increase in family isolation, unemployment, and economic stress, the pandemic increased domestic violence calls by 7.5% from March to May, 2020.

Faced with this major challenge for the world economy, Welfens (2020) highlights that a broader and deeper analytical link between macroeconomic approaches and health system analysis seems to be adequate. Moreover, macroeconomic sectors tend to suffer strong and asymmetric impacts in every crisis. Studies such as Kaplan et al. (2020) that measure the effect of the fall in housing net worth on household expenditures during the Great Recession, or Aloui et al. (2020), that propose assessing the impact of COVID-19 shocks on the energy futures markets on crude oil and natural gas, can be useful to predict the impacts of the current crisis on macroeconomic environment.

In this debate, we add to the discussion on the economic effects of COVID-19, aligned to Wu et al. (2020), by proposing to measure the impact of COVID-19 on the US stock market. We are the first, to our knowledge, to assess the relationship in the time-frequency domain between the cases or deaths by COVID-19 in Hubei, China, in countries with record deaths and in the world and the return on S&P 500 and its sector indices.

In a turbulent semester in US for political reasons or for oil fluctuations, we analyze not only the impact of COVID-19, but also sectoral transmission, controlling for a specific set of instruments, lagged Fama and French (2015) 5 factors. In terms of sample size, the main limitation for the time-series span used here is due to the reality of the pandemic: it is still very recent, and it lasted a short time. We use the largest possible set of variables, covering the period from January 29 to June 30, 2020, at a daily frequency. The data sources are Investing.com and Johns Hopkins Corona Virus Research Center.

Since our purpose is to study when and at what frequencies each COVID-19 variable is synchronized or not with S&P 500, besides the co-movements between sector indices in US, we follow methodologically Aguiar-Conraria et al. (2018), by using partial wavelet coherencies, partial phase-difference diagrams, and partial gains. This mathematical framework enables us to infer on which financial cycle has been leading or lagging each disease cycle. Based on the wavelet transforms, we can also explore sectoral contagion, based on dissimilarities, Granger causality and coherencies between S&P sector indices. Our findings are useful to tell the history of the pass-through of this recent health crises across the sectors of the US economy.

The layout of the paper is the following: Section 2 provides a literature review; Section 3 outlines the methodology; Section 4 describes the data and presents the results; Section 5 offers some concluding remarks.

## 2. Literature Review

According to wavelet researchers, by using this framework, we are adopting a whole new perspective in processing data, although the idea behind this technique has existed since 1800s. This methodology is well suited to our intent because it is a useful mathematical approach to describe in a very simple way the conditional synchronization and transmission of the pandemic cycles to financial cycles.

This methodology – widely used in some areas, as physics and medicine – has also been used in economics, and in finance, mainly in the last decade. We have listed below some very recent correlated contributions.

Bera et al. (2020) find that the effects of risk factors on average returns vary over the time scales by their coefficient magnitudes and statistical significance, based on the wavelet multiscaling approach, for the period from July 1963 to February 2018. This contribution has motivated us to use such 5 factors to control the co-movements in the partial framework. Related to our purpose, i.e. the effects of coronavirus pandemic, Wu et al. (2020) use the coherence wavelet method and the wavelet-based Granger causality tests applied to US recent daily. They find that COVID-19 risk is perceived differently over the short and the long-run and may be firstly viewed as an economic crisis, for the period from January 21 to March 30, 2020.

Regarding recent contributions using partial wavelet framework, Matos et al. (2020) address frequency-varying co-movements involving finance variables. They assess the relationship in the time-frequency domain between household credit market variables (growth and delinquency rates for consumer loans and home mortgages) and macro-finance variables in the U.S: the growth of real income, wealth, and consumption expenditures on services, nondurable, and durable goods, and the real return on U.S. major stock indices.

Sharif et al. (2020) employ partial- and multiple-wavelet coherence analyses to find that crude oil price has had a considerable effect on co-movement between oil-importing and oil-exporting countries but has had limited effects on co-movement in oil-importing countries and limited effects of co-movement in oil-exporting countries, for period from January 1 to December 29, 2017. We follow this interesting contribution, in the sense of comparing the coherence with and without a specific instrument, which enables us to infer on the relevance of COVID-19 variables US as a control in sectoral contagion in US.

## 3. Methodology

The wavelet transforms originally explored empirically by Grossmann and Morlet (1984) are a useful tool to deal with financial data, usually noisy, nonstationary, and nonlinear. This method is well suited to our intent, since it enables us to trace transitional changes across time and frequencies, improving the analysis of cycles on the comparison to the traditional methods. We follow most of the recent empirical contributions, as Matos et al. (2020) by using Morlet as the continuous complex-valued mother wavelet. This function is ideal for the analysis of oscillatory signals since it provides an estimate of the instantaneous amplitude and instantaneous phase of the signal in the vicinity of each time/frequency location $(\tau, s)$.

According to this method, we measure the dissimilarity between a pair of given wavelet spectra based on

$$dist(W_x, W_y) = \frac{\sum_{k=1}^{K} w_k^2 [d(\mathrm{l}_x^k, \mathrm{l}_y^k) + d(\mathbf{u}_k, \mathbf{v}_k)]}{\sum_{k=1}^{K} w_k^2} \tag{1}$$

The wavelet transforms of $x$ and $y$ are given by $W_x(.)$ and $W_y(.)$, respectively. Moreover, $w_k^2$ are the weights equal to the squared covariance explained by each axis, $\mathbf{u}_k$ and $\mathbf{v}_k$ are singular vectors satisfying variational properties and $\mathrm{l}_x^k$ and $\mathrm{l}_y^k$ are leading patterns. K is the number of singular vectors used to capture the covariance in the data. In this work we used K=3 for all computations of dissimilarities. The full description of the dissimilarity measure used is provided by Aguiar-Conraria and Soares (2011).

The cross-wavelet transform and the respective wavelet coherency of $x(t)$ and $y(t)$ are defined as

$$W_{xy}(\tau, s) = W_x(\tau, s)\overline{W_y}(\tau, s) \tag{2}$$

and

$$R_{xy}(\tau, s) = \frac{|S(W_{xy}(\tau,s))|}{\sqrt{S(|W_{xx}(\tau,s)|)S(|W_{yy}(\tau,s)|)}}, \tag{3}$$

where $S(.)$ is a smoothing operator in scale and time.

As usual, we analyze the time-frequency dependencies, by using phase-difference, given by

$$\phi_{xy}(s, \tau) = tan^{-1}\left(\frac{\Im(W_{xy}(s,\tau))}{\Re(W_{xy}(s,\tau))}\right), \tag{4}$$

where $\Re(.)$ and $\Im(.)$ are the real and the imaginary parts of the cross wavelet spectrum.

Our purpose is to discuss the synchronization and the lead-lag conditional relationships between COVID-19 cases or deaths and financial variables. However, we aim to do that, assuming that other variables fluctuated in the first half of 2020. In other words, besides allowing for the variation of coefficients along with time and frequencies, we want to control each pairwise co-movement for a specific vector of instruments, $\boldsymbol{z}$.

We follow Aguiar-Conraria et al. (2018), by using the partial wavelet framework. Hence, the multiple wavelet coherency between $y$ and the series $x$ and $\boldsymbol{z}$, denoted by $R_{y(x\boldsymbol{z})}$ is given by

$$R_{y(x\boldsymbol{z})} = \sqrt{\frac{R_{yx}^2 + R_{yz}^2 - 2\Re(\xi_{yx}\xi_{xz}\overline{\xi_{yz}})}{1-R_{xz}^2}} \tag{5}$$

The partial wavelet coherency between $y$ (index) and $x$ (COVID-19) after controlling for $\boldsymbol{z}$ is given by

$$\xi_{yx,\boldsymbol{z}} = \frac{\xi_{yx} - \xi_{yz}\overline{\xi_{xz}}}{\sqrt{(1-R_{yz}^2)(1-R_{xz}^2)}} \tag{6}$$

The absolute value and the angle of $\xi_{yx,\boldsymbol{z}}$ are respectively the partial wavelet coherency and the partial wavelet phase difference between $y$ and $x$, after controlling for $\boldsymbol{z}$. They are analog of the bivariate metrics given by (3) and (4), and they are denoted by $R_{yx,\boldsymbol{z}}$ and $\phi_{yx,\boldsymbol{z}}$. Regarding the signs, a phase-difference of zero indicates that the time-series move together at the specified frequency. If $\phi_{yx,z} \epsilon \left(0, \frac{\pi}{2}\right)$ the series move in phase, but the time-series $y$ leads $x$, while if $\phi_{yx,z} \epsilon \left(-\frac{\pi}{2}, 0\right)$ then it is $x$ that is leading. A phase-difference of $\phi_{yx,z} = \pm\pi$ indicates an anti-phase relation. Finally, if $\phi_{yx,z} \epsilon \left(\frac{\pi}{2}, \pi\right)$, then $x$ is leading and time-series $y$ is leading if $\phi_{yx,z} \epsilon \left(-\pi, -\frac{\pi}{2}\right)$. We also follow Aguiar-Conraria et al. (2018), by using their general concept of wavelet gain (coefficient regression) by defining the partial wavelet gain, which can be interpreted as a regression coefficient in the regression of $y$ on $x$, after controlling for $\boldsymbol{z}$, given by

$$G_{yx,\boldsymbol{z}} = \frac{|\xi_{yx} - \xi_{yz}\overline{\xi_{xz}}|}{(1-R_{xz}^2)} \frac{\sigma_y}{\sigma_x} \tag{7}$$

We also test causality between the COVID-19 metrics and the S&P 500 return, performing a parametric test for Granger-causality in quantiles developed by Troster (2018), whose critical values are estimates by the subsampling procedure based on Sakov and Bickel (2000). The key advantage it is the possibility to capture tail-dependence between series, which cannot be measured by the traditional Granger (1969) tests in a mean.

## 4. Data and empirical results

In terms of sample size, the main limitation for the time-series span is due to the pandemic duration. We use the largest possible set, covering the period from January 29 to June 30, 2020, at a daily frequency.

Health data set is comprised by series of deaths and cases of COVID-19 in the most affected countries until June 30, 2020: US, Brazil, United Kingdom, Italy, and France. We also use data from China and Hubei Province to analyze early stages. Based on Ding et al. (2020), we use daily log growth of 7-days moving average of new cases and deaths as our final explanatory variables.[2] This transformation account for weekends, holidays, week seasonality and outliers in the data. The data source is the Center for Systems Science and Engineering (CSSE) at Johns Hopkins University (JHU). For more details, see Dong, Du, and Gardner (2020).

[2] We define log growth, $r_t$, of 7-days moving average of $x_t$ on t as follows: $r_t = ln\left(1 + MA7(x_t)\right) - ln\left(1 + MA7(x_{t-1})\right)$, where $MA7(x_t)$ stands for the moving average of $x_t$ on t.

Concerning the financial variables, we use daily returns on S&P 500 and its 11 sector indices. The sector indices are formed by the companies included in the S&P 500 index and classified as members of each of the 11 specific sectors under the Global Industry Classification Standard (GICS). In our main empirical exercises, we control for a specific set of instruments, lagged Fama and French (2015) 5 factors (FF5F). The data sources are Investing.com and Professor Kenneth French Research Data Library.

Figure 1.a suggests a pattern of convergence, even in an atypical period, characterized by market turbulence. We highlight that only the consumer discretionary and the information technology sectors had cumulative gains in the period. The biggest drawdown recorded was in the energy sector. The cases for covid-19 in the selected locations (Figure 1.b) seem to have reached the plateau, while deaths worldwide and in the US still show increasing moving averages at the end of June 2020 (Figure 1.c). Summary statistics of such COVID-19 variables, such as lethality and mortality are reported in Table 1 (Panel C).

In the Table 1 (Panel A), we highlight, based on Morlet dissimilarities, the synchronization between return on S&P 500 and deaths in Italy, significant at 5%, and deaths and cases in US, significant at 10%.

Also, in the Table 1 (Panel B), we report the results of the Granger causality test in quantiles.

Given that stock returns during crises are very volatile and causal relations among the series are non-linear, we evaluate the causal relations in the extreme tails of the conditional distribution. The most interesting results are associated with the largest losses in the market. We highlight the predictive power of deaths in Hubei and China, while deaths in Brazil also seem to be useful in predicting the movement of the S&P 500 at median values. Market returns seem to predict the dynamics of the number of cases in some countries, based on the first decentile.

Based on these finding in terms of synchronization and forecasting, we perform our first exercise, aiming to see how COVID-19 deaths and cases in different localities are related to returns on S&P 500 one day ahead. We report the results for the most relevant series on Figure 2. The partial wavelet coherencies are plotted as 2-dimensional heat-maps. The colors range from blue (small coherency) to red (high coherency) and the cone of influence is shown with a black line. In the partial phase-difference and gain diagrams, we display mean values corresponding to three frequency intervals: 2∼4 days (short cycles), 4∼8 days (medium-term fluctuations) and 8∼16 days (long-run relationships). Considering all 16 possibilities involving S&P 500 and cases or deaths in each of the chosen locations, we plot only the figures and the diagrams with a higher incidence of regions with strong partial coherency.

We emphasize the relevance of cases and deaths in Europe and the US, while COVID-19 data in China and Brazil do not have significant systemic coherence. More specifically, we find that over the period from February to June, there is a systemic and robust incidence of areas with strong high frequency coherence, i.e., the significance of short-term co-movements considering S&P 500 and cases in US, as well as deaths in France, Italy, US and world. We observe longer term coherence between S&P 500 cycles and the cycles of cases and deaths in UK during the months of March and April, while cases in US have strong coherence with US stock market during almost the whole period.

Considering only short-term cycles (2~4days), from a chronological analysis, the cycles of deaths in Italy in the first days of March and soon afterwards, cycles of deaths in the world are able to lead the cycles of the US stock market index, intuitively out-of-phase, with partial gains ranging from 0.2 and 0.3.

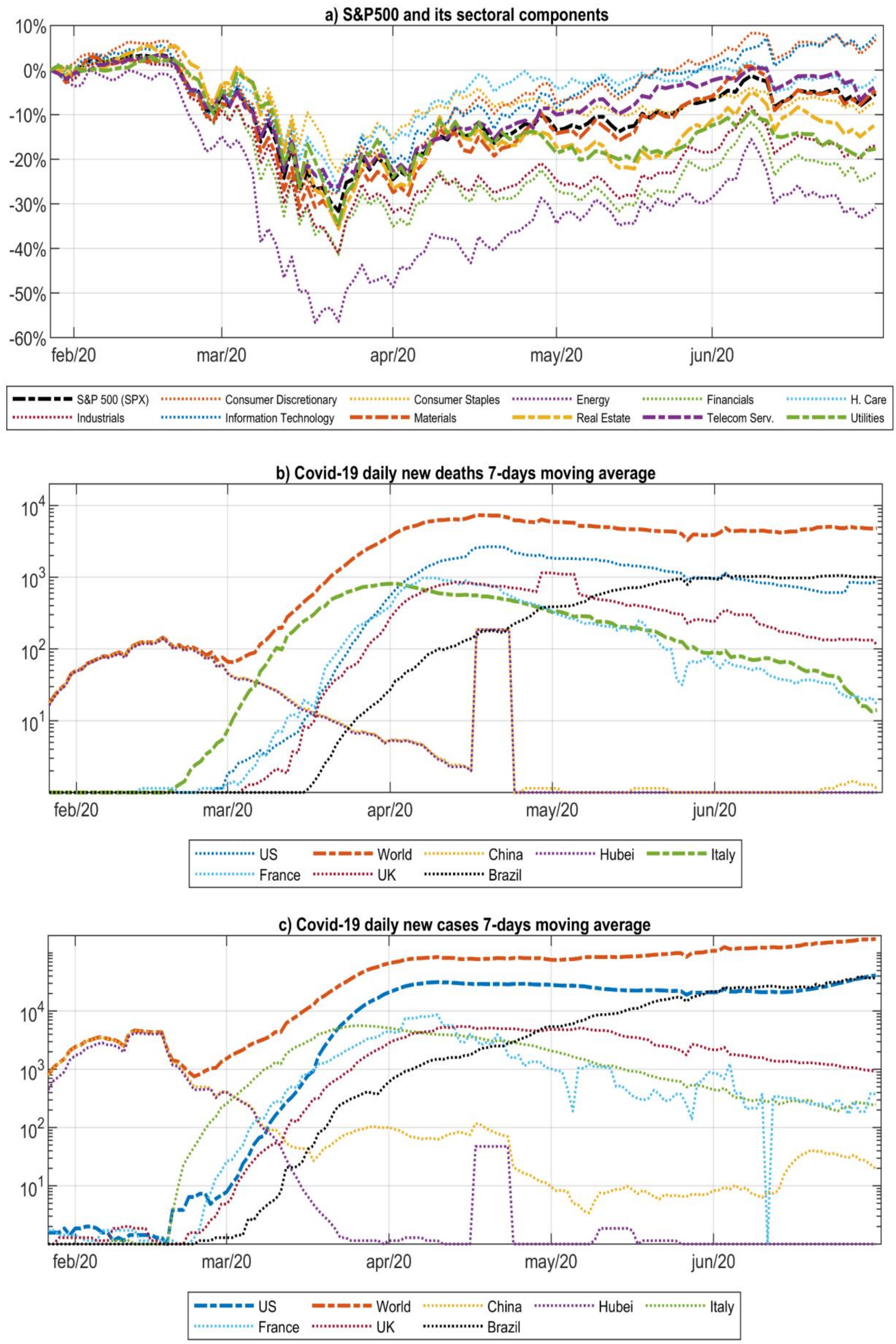


**Figure 1:** Cumulative return on S&P 500 and S&P sector indices, and COVID-19 numbers worldwide. [a]

Notes: [a] Data from January 29 to June 30, 2020. Source: Investing.com and Johns Hopkins Corona Virus Research Center.

**Table 1:** US stock market and COVID-19 numbers worldwide.[a, b, c]

| | | COVID-19 variables | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Deaths | | | | | | | | Cases | | | | | | | |
| | | US | World | China | Hubei | Italy | France | UK | Brazil | US | World | China | Hubei | Italy | France | UK | Brazil |
| **Panel A. Dissimilarities** | | | | | | | | | | | | | | | | | |
| S&P 500 (SPX) | | 0.42* | 0.51 | 0.41 | 0.40 | 0.42** | 0.59 | 0.45 | 0.60 | 0.43* | 0.59 | 0.52 | 0.45 | 0.49 | 0.72 | 0.48 | 0.53 |
| **Panel B. Granger causalities** | | | | | | | | | | | | | | | | | |
| S&P 500 (SPX) median 0.50 | COVID → Index | [0.73] | [0.68] | [0.57] | [0.27] | [0.66] | [0.70] | [0.32] | **[0.05]** | [0.70] | [0.74] | [0.79] | [0.42] | [0.65] | [0.63] | [0.58] | [0.36] |
| | Index → COVID | **[0.10]** | [0.36] | [0.99] | [0.92] | [0.75] | [0.32] | [0.28] | **[0.03]** | **[0.01]** | [0.15] | [0.64] | **[0.08]** | **[0.02]** | [0.22] | **[0.02]** | **[0.02]** |
| S&P 500 (SPX) quantil 0.10 | COVID → Index | [0.73] | [1.00] | **[0.07]** | **[0.04]** | [0.71] | [0.72] | [0.66] | [0.10] | [0.59] | [0.78] | [0.60] | **[0.08]** | [0.72] | [0.69] | [0.55] | [0.66] |
| | Index → COVID | [0.41] | [1.00] | [0.46] | [0.62] | **[0.02]** | [0.24] | [0.17] | [0.46] | **[0.01]** | **[0.01]** | **[0.01]** | **[0.08]** | **[0.02]** | **[0.02]** | **[0.02]** | [0.38] |
| S&P 500 (SPX) quantil 0.90 | COVID → Index | **[0.10]** | **[0.01]** | [0.68] | [0.65] | **[0.09]** | **[0.10]** | [0.11] | **[0.03]** | **[0.01]** | **[0.01]** | **[0.01]** | [0.92] | **[0.09]** | **[0.09]** | **[0.08]** | [0.11] |
| | Index → COVID | [0.88] | [0.42] | [0.61] | [0.15] | [0.79] | [0.86] | **[0.02]** | [0.21] | [0.38] | **[0.01]** | [0.29] | **[0.08]** | [0.81] | **[0.02]** | [0.25] | [0.40] |
| **Panel C. Coronavirus Disease** | | | | | | | | | | | | | | | | | |
| Lethality (deaths to cases) | | 4.8% | 4.9% | 5.5% | 6.6% | 14.5% | 15.3% | 14.0% | 4.3% | - | - | - | - | - | - | - | - |
| Mortality (deaths per million inhabitants) | | 384.6 | 65.5 | 3.2 | 76.3 | 575.6 | 455.8 | 644.0 | 280.1 | - | - | - | - | - | - | - | - |
| Total deaths (thousands) | | 127.4 | 511.3 | 4.6 | 4.5 | 34.8 | 29.8 | 43.7 | 59.6 | - | - | - | - | - | - | - | - |
| Mean (Daily Log Growth - 7 Days Mov. Aver.) | | 4.8% | 3.7% | -1.3% | -1.4% | 2.0% | 2.4% | 3.0% | 4.6% | 6.2% | 3.4% | -2.3% | -3.9% | 2.6% | 3.3% | 4.0% | 6.3% |
| St. dev. (Daily Log Growth - 7 Days Mov. Aver.) | | 12.7% | 9.4% | 8.9% | 8.7% | 12.2% | 17.0% | 16.1% | 8.7% | 14.7% | 12.0% | 17.4% | 18.1% | 13.8% | 88.3% | 14.9% | 10.6% |

Notes: [a] Data from January 29 to June 30, 2020. [b] Dissimilarities between S&P 500 and the explanatory variables (deaths and cases of COVID-19). * p-value < 0.10, ** p-value < 0.05 and *** p-value < 0.01, derived from Monte Carlo Simulations with 5000 runs assuming red noise as a null hypothesis. [c] Granger-causality in quantiles are based on Troster (2018). We perform the quantile regression with 3 lags of the dependent variable. P-value reported in the brackets. Source: Investing.com and Johns Hopkins Corona Virus Research Center.

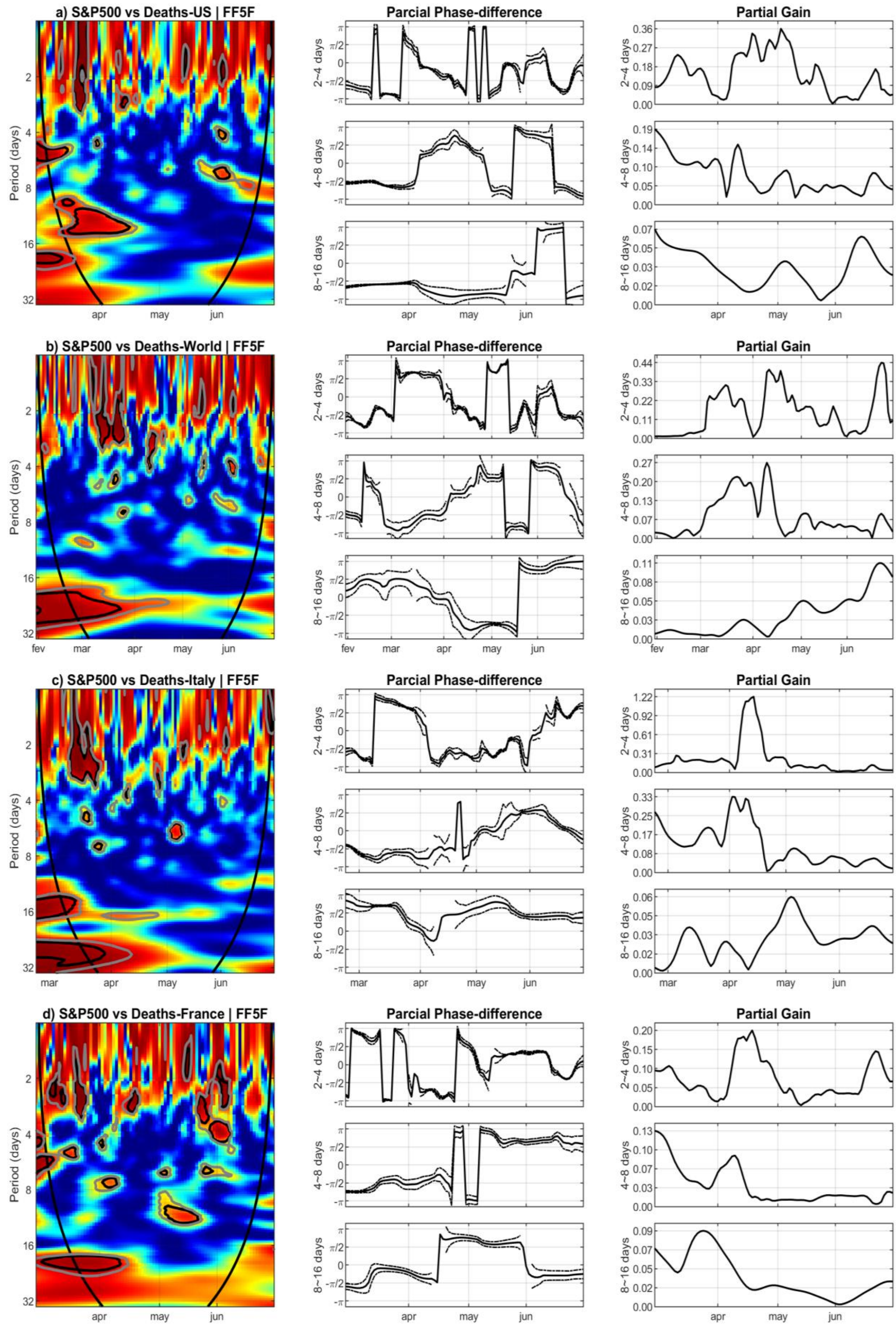


**Figure 2**: Partial wavelet framework of S&P 500 vs COVID-19 controlled by lagged Fama and French (2015) 5 factors.

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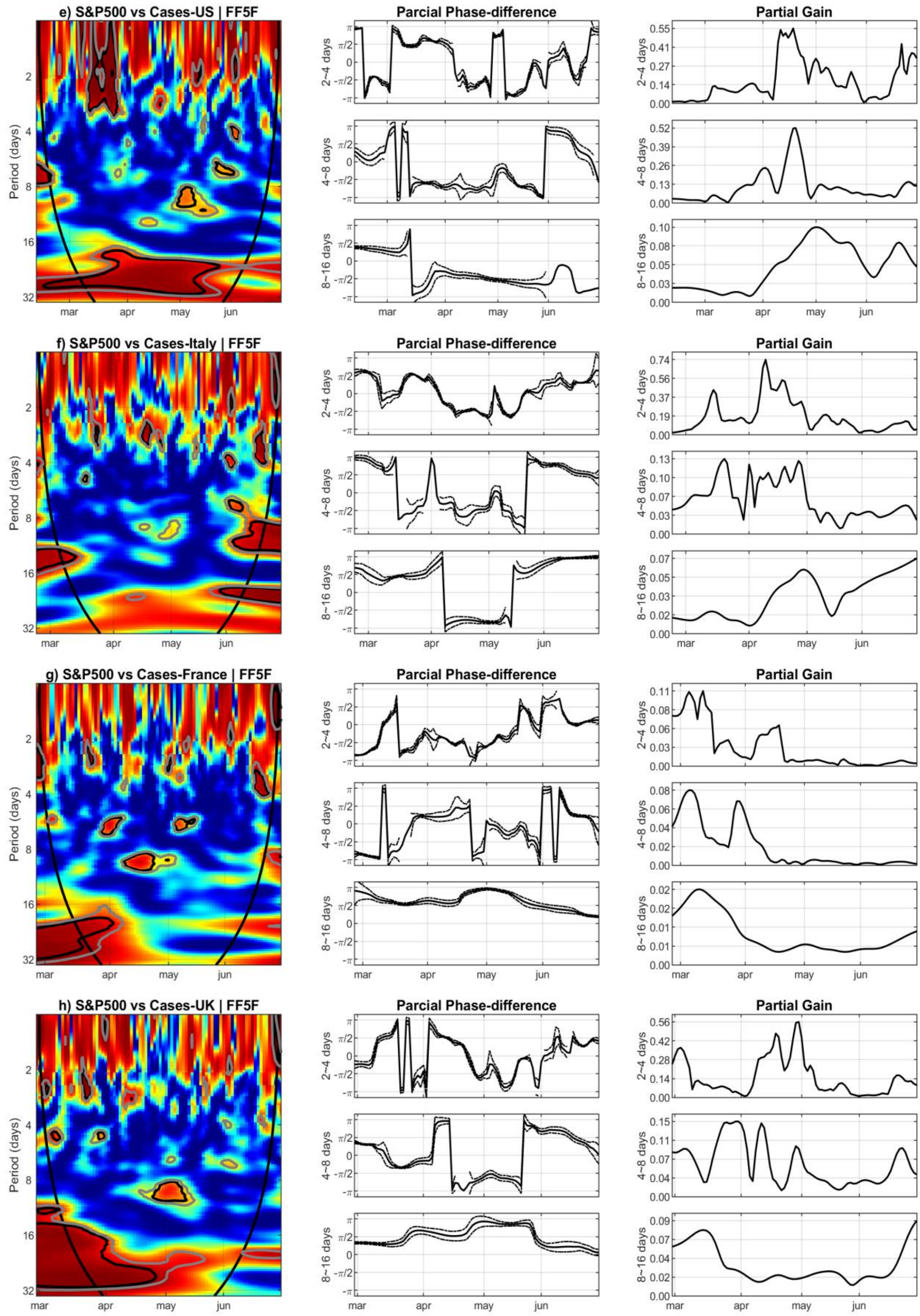


**Figure 2**: Partial wavelet framework of S&P 500 vs COVID-19 controlled by lagged Fama and French (2015) 5 factors.
Notes: [a] The cone of influence is shown as the black convex curve. The 5% significance level contours are in black, the 10% in gray and both are derived from Monte Carlo Simulations with 5000 runs assuming red noise as a null hypothesis. [b] Data from January 29 to June 30, 2020. Source: Investing.com and Johns Hopkins Corona Virus Research Center.

There is also an anti-phase relation between cycles of return on S&P 500 and deaths in US during the second half of March, with no leadership and partial gain close to zero.

Analyzing the low frequency co-movements (8~16 days), we find that the cycles of the US market index in the first half of April are useful to anticipate in an anti-phasic way the cycles of deaths in the US, with seemingly null partial gain. This finding is aligned to the results of Sharif et al. (2020), who shows that US stock Granger cause the US cases (2-4 days and 4-8 days). Finally, in the first half of May 2020, S&P 500 cyclers are out-of-phase lagging the cycles of deaths in France, with no partial reaction.

This analysis suggests a chronological sequence, such that only after the release of news of the increase in deaths in Italy, then in the world and finally in the US, S&P 500 reacted through a negative and significant co-movement. In other words, the crisis was priced via a drop in the S&P 500, following this path of deaths.

Although all economic sectors have experienced extreme volatility during the COVID-19 driven stock market crash, previous studies have reported asymmetric effects on market returns of the sector indices of US (Mazur, Dang and Vega, 2020).

In this context, a natural question is: what is the crisis pass-through among the economic sectors in US?

In our second exercise, we propose evaluating the sectoral contagion between S&P sector indices during the pandemic spread. In the first step we test Granger causality based on VAR among the sector indices, conditional to the lagged FF5F.

According to the results reported in Table 2 (Panel C), based on S&P sector indices, the first sector to react to the pandemic is the energy sector, which Granger causes the market index and this one Granger causes the sectors of telecom and utilities. We are also able to show that there are direct contagions between sectors. Energy sector cycles are useful to predict health care cycles. Industrial sector is able to predict the financial sector, which seems to be able to forecast the cycles of the telecom and utilities sectors. Telecom cycles are also predicted by the cycles of materials and real estate sectors. It is worth mention that the sector indices that triggered out financial contagion were the most affected during this period – based on risk metrics –, indicating the importance of the COVID-19 spread in those causal relations.

According to the dissimilarities reported in Table 2 (Panel D), the co-movements among the US sector indices have been stronger during COVID-19 pandemic as compared to the end of 2019. We find that the average distance between the sector indices is 0.31 at 2020, 4.7 points less than in 2019 (0.357).

Finally, we also propose better understanding the role of the COVID-19 not only in the stock market but also in the causal relations among the sectors. Aiming to complement our contagion analysis, we use the partial coherence with two different sets of controls for each of the six pair of sectors with significant Granger causality. First, we use lagged FF5F as controls, and then we use FF5F in addition to COVID-19 series (deaths in Italy and cases in US). We report the results in Figure 3.

We find that materials vs telecom, real estate vs telecom and financials vs utilities have considerably less (from 11.2% to 18%) significant area on the second configuration partial coherence. This result suggests that the COVID-19 have been reinforcing the co-movement of those pairs of sectors. To financials vs telecom, we find a growth of 15.6% on the significant area on second configuration. This suggests that COVID-19 has contributed to weaken the co-movement of this pair of sectors. For the two remaining pairs of sectors the change was also positive but less pronounced (3 – 4.5%).

**Table 2.** Summary statistics, dissimilarities and Granger causality of S&P 500 and its sector indices.

**Panel A: Summary statistics of US sector indices**

| Statistics | SPLRCD | SPLRCS | SPNY | SPSY | SPXHC | SPLRCI | SPLRCT | SPLRCM | SPLRCREC | SPLRCL | SPLRCU |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Cumulative return | 6.80% | -7.30% | -30.80% | -23.00% | -1.60% | -16.90% | 7.90% | -4.70% | -12.20% | -3.60% | -17.70% |
| Standard deviation | 2.90% | 2.60% | 5.00% | 4.10% | 2.80% | 3.60% | 3.50% | 3.40% | 3.70% | 2.80% | 3.60% |
| Market beta | 0.89 | 0.74 | 1.37 | 1.25 | 0.83 | 1.08 | 1.1 | 1.04 | 1.09 | 0.85 | 0.99 |
| Drawdown | 28.20% | 22.80% | 56.70% | 41.40% | 26.60% | 41.10% | 27.30% | 35.10% | 35.60% | 26.20% | 34.60% |

**Panel B: Dissimilarities and Granger causality, respectively, between S&P 500 and US sector indices**

| Indices | | SPLRCD | SPLRCS | SPNY | SPSY | SPXHC | SPLRCI | SPLRCT | SPLRCM | SPLRCREC | SPLRCL | SPLRCU |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| S&P 500 (SPX) | | 0.20*** | 0.27*** | 0.25*** | 0.18*** | 0.24*** | 0.19*** | 0.15*** | 0.19*** | 0.28*** | 0.16*** | 0.35* |
| S&P 500 (SPX) | Sector index → Index | 0.9 | 0.68 | 0.23 | **0.09** | 0.68 | 0.18 | 0.11 | 0.77 | 0.94 | 0.91 | 0.87 |
| S&P 500 (SPX) | Index → Sector index | 0.61 | 0.52 | 0.59 | 0.67 | 0.24 | 0.26 | 0.56 | 0.46 | 0.94 | **0.01** | **0.09** |

**Panel C: Granger causality between US sector indices Obs.: Sector index (row) Granger causes sector index (column)**

| Indices | SPLRCD | SPLRCS | SPNY | SPSY | SPXHC | SPLRCI | SPLRCT | SPLRCM | SPLRCREC | SPLRCL | SPLRCU |
|---|---|---|---|---|---|---|---|---|---|---|---|
| S&P 500 Consumer Discretionary (SPLRCD) | - | 0.2 | 0.29 | 0.42 | 0.38 | 0.16 | 0.91 | 0.24 | 0.9 | 0.93 | 0.96 |
| S&P 500 Consumer Staples (SPLRCS) | 0.61 | - | 0.8 | 0.51 | 0.13 | 0.45 | 0.13 | 0.25 | 0.93 | 0.32 | 0.43 |
| S&P 500 Energy (SPNY) | 0.54 | 0.82 | - | 0.62 | **0.02** | 0.75 | 0.85 | 0.12 | 0.36 | 0.87 | 0.67 |
| S&P 500 Financials (SPSY) | 0.71 | 0.59 | 0.97 | - | 0.58 | 0.86 | 0.6 | 0.38 | 0.57 | **0.03** | **0.08** |
| S&P 500 Health Care (SPXHC) | 0.62 | 0.98 | 0.91 | 0.75 | - | 0.38 | 0.58 | 0.52 | 0.43 | 0.27 | 0.73 |
| S&P 500 Industrials (SPLRCI) | 0.31 | 0.92 | 0.74 | **0.01** | 0.13 | - | 0.73 | 0.3 | 0.71 | 0.15 | 0.45 |
| S&P 500 Information Technology (SPLRCT) | 0.25 | 0.88 | 0.78 | 0.81 | 0.24 | 0.16 | - | 0.34 | 0.65 | 0.77 | 0.18 |
| S&P 500 Materials (SPLRCM) | 0.59 | 0.62 | 0.6 | 0.3 | 0.22 | 0.95 | 0.86 | - | 0.84 | **0.07** | 0.73 |
| S&P 500 Real Estate (SPLRCREC) | 0.77 | 0.57 | 0.57 | 0.93 | 0.44 | 0.67 | 0.93 | 0.98 | - | **0.05** | 0.95 |
| S&P 500 Telecom Services (SPLRCL) | 0.56 | 0.27 | 0.11 | 0.22 | 0.51 | 0.15 | 0.13 | 0.12 | 0.72 | - | 0.22 |
| S&P 500 Utilities (SPLRCU) | 0.98 | 0.86 | 0.47 | 0.6 | 0.2 | 0.71 | 0.53 | 0.48 | 0.42 | 0.23 | - |

**Panel D: Dissimilarities 2019 (upper triangle) and 2020 (lower triangle) between US sector indices**

| Indices | SPLRCD | SPLRCS | SPNY | SPSY | SPXHC | SPLRCI | SPLRCT | SPLRCM | SPLRCREC | SPLRCL | SPLRCU |
|---|---|---|---|---|---|---|---|---|---|---|---|
| S&P 500 Consumer Discretionary (SPLRCD) | - | 0.43 | 0.37** | 0.30*** | 0.41 | 0.33** | 0.32** | 0.35** | 0.46 | 0.34** | 0.50 |
| S&P 500 Consumer Staples (SPLRCS) | 0.39 | | 0.51 | 0.44 | 0.40 | 0.47 | 0.43 | 0.46 | 0.35** | 0.45 | 0.33*** |
| S&P 500 Energy (SPNY) | 0.31*** | 0.39 | | 0.28*** | 0.38* | 0.31*** | 0.41* | 0.30*** | 0.52 | 0.49 | 0.47 |
| S&P 500 Financials (SPSY) | 0.29*** | 0.29*** | 0.22*** | | 0.37* | 0.28*** | 0.34** | 0.29*** | 0.44 | 0.34** | 0.45 |
| S&P 500 Health Care (SPXHC) | 0.37 | 0.29*** | 0.36* | 0.29*** | | 0.38** | 0.33** | 0.37** | 0.44 | 0.38* | 0.43 |
| S&P 500 Industrials (SPLRCI) | 0.28*** | 0.31** | 0.23*** | 0.19*** | 0.32** | | 0.31*** | 0.25*** | 0.45 | 0.38** | 0.49 |
| S&P 500 Information Technology (SPLRCT) | 0.22*** | 0.35 | 0.32** | 0.28*** | 0.29** | 0.29*** | | 0.32** | 0.41 | 0.31*** | 0.41* |
| S&P 500 Materials (SPLRCM) | 0.29*** | 0.30*** | 0.30*** | 0.22*** | 0.29*** | 0.21*** | 0.27*** | | 0.49 | 0.35** | 0.45 |
| S&P 500 Real Estate (SPLRCREC) | 0.33** | 0.32** | 0.36** | 0.28*** | 0.38 | 0.27*** | 0.34* | 0.30*** | | 0.48 | 0.34** |
| S&P 500 Telecom Services (SPLRCL) | 0.23*** | 0.33* | 0.30*** | 0.28*** | 0.30** | 0.29*** | 0.18*** | 0.26*** | 0.35* | | 0.42 |
| S&P 500 Utilities (SPLRCU) | 0.43 | 0.29*** | 0.43 | 0.36* | 0.35* | 0.37* | 0.44 | 0.36* | 0.28*** | 0.41 | |

Notes: [a] Panel D uses data from July to December, 2019 and from January to June, 2020. The remaining data is from January 29 to June 30, 2020. [b] Dissimilarities between S&P 500 and the explanatory variables (deaths and cases of COVID-19). * p-value < 0.10, ** p-value < 0.05 and *** p-value < 0.01, derived from Monte Carlo Simulations with 5000 runs assuming red noise as a null hypothesis. [c] Granger-causality based on a conditional VAR, the number of lags is set by HQ criteria (max lags= 5). P-values are reported (values less than .10 in Bold). Source: Investing.com and Johns Hopkins Corona Virus Research Center.

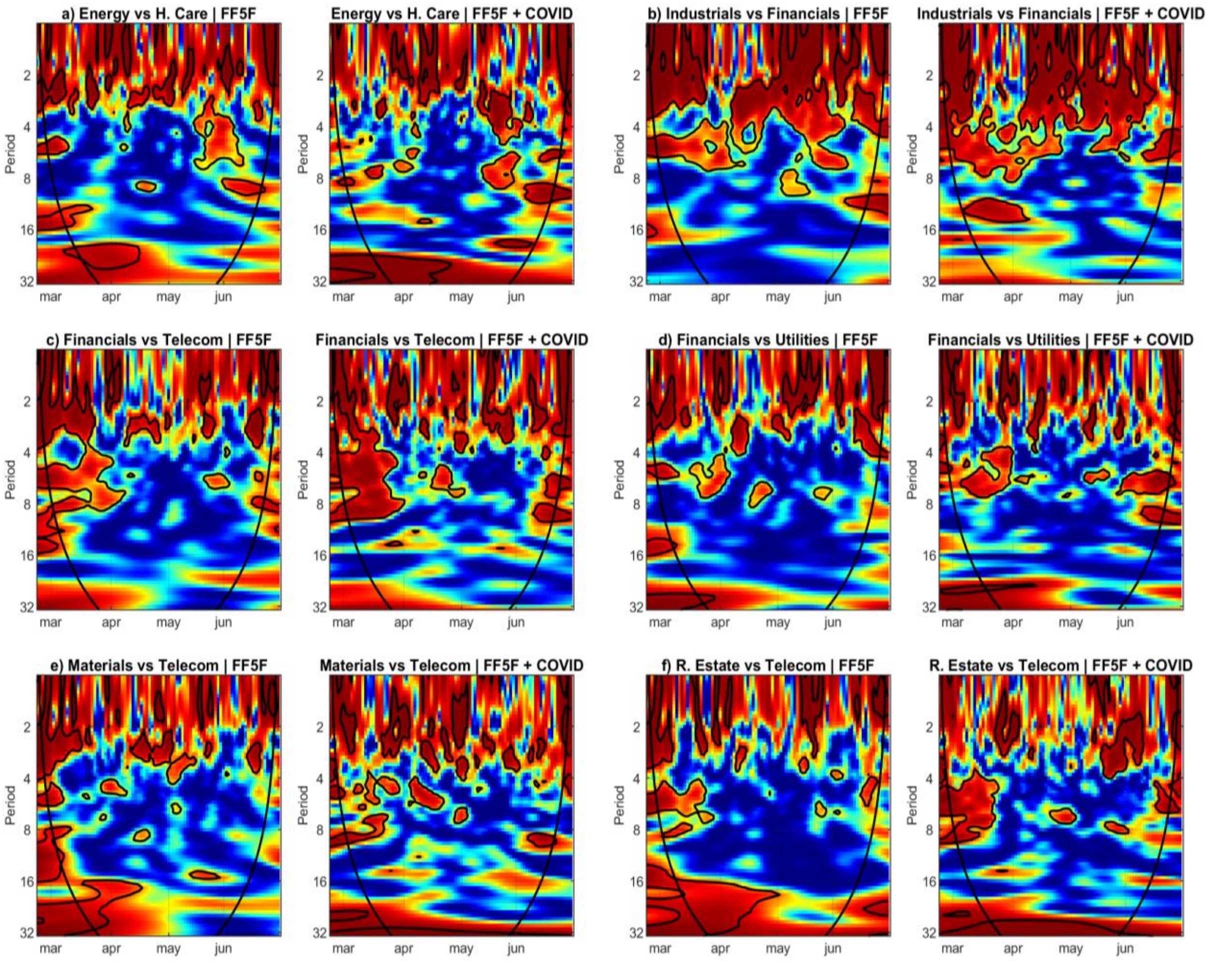


**Figure 3**: Partial wavelet of selected pair of sector indices controlled by lagged Fama and French (2015) 5 factors (FF5F), left, and lagged FF5F and COVID-19 series represented by Italy deaths and US Cases, right.
Notes: [a] The cone of influence is shown as the black convex curve. The 10% significance level contours are also in black and are derived from Monte Carlo Simulations with 5000 runs assuming red noise as a null hypothesis. [b] Data from February 23 to June 30, 2020. Source: Investing.com and Johns Hopkins Corona Virus Research Center.

## 5. Conclusion

We revisit the debate promoted by Wu et al. (2020), by assessing the conditional relationship in the time-frequency domain between the cases or deaths by COVID-19 in Hubei, China, in countries with record deaths and in the world and the return on S&P 500, for the period from January 29 to June 30, 2020. We believe having offered useful findings to the financial market, such as the significant predictive power of deaths in Hubei and China based on the quantile Granger causality (left tail of the conditional distribution), for instance, or the evidence that short-term cycles of deaths in Italy in the first days of March and soon afterwards, cycles of deaths in the world are able to lead out-of-phase cycles of the US stock market index. We also invite researchers and policy makers to use the information that the low frequency cycles of the US market index in the first half of April are useful to anticipate in an anti-phasic way the cycles of deaths in the US.

Moreover, we propose identifying the sector pass-through of this crisis in US and the specific role of COVID-19 in this transmission channel. Our findings on the sectoral contagion based on Granger causalities and partial wavelet coherencies between S&P sector indices are useful to draw public policies to safeguard financial stability and to analyze the timing of the impact of the pandemic crises in each sector.

The strategic role of the energy sector, which first reacted to the pandemic and presented the highest values of losses and volatility, or the evidence about the telecom sector, whose oscillations can be predicted by several other sectors, are findings useful and that can be compared to the role of countries transparency in the global transmission of financial shocks promoted by Brandao-Marques et al. (2018).

Given the importance of transparency to mitigate undesirable financial markets effects during a health crisis, our findings advise for more frequent and reliable health numbers handling for the public policy makers as a non-financial and potentially cheaper measure to avoid as much as possible panic in financial markets during health driven crisis. Since foreign numbers seem to be important to explain US financial market fluctuations, our paper also stresses the importance of cooperation in international level to ensure global quality and availability on heath data.

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