On the relationship between COVID-19 and Brazilian financial market

Antônio Costa [a,1], Cristiano da Silva [a], Paulo Matos [a]
[a] *CAEN Graduate School of Economics, Brazil*

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ABSTRACT

Brazil is a record holder among emerging economies in terms of cases and deaths by COVID-19. In our first empirical exercise, we follow Aguiar-Conraria et al. (2018) aiming to assess the conditional relationship in the time-frequency domain between the return on Ibovespa and the cases or deaths by COVID-19 in Hubei, countries with record deaths and the world, for the period from January 29 to July 31, 2020. We also perform a parametric test for Granger-causality in quantiles developed by Troster (2018). Second, we study Brazilian sectoral contagions and pass-through by using Granger causality and by performing a wavelet-based Value-at-risk proposed by Rua and Nunes (2009). Our findings are useful to infer on when COVID-19 cycles started to impact Ibovespa cycles and to tell the history of the pass-through of this pandemic across the economic sectors

1. Introduction

Since the end of 2019, a respiratory disease of seemingly unknown cause identified in the Chinese city of Wuhan has evolved into a truly global pandemic. Less than a year later, society worldwide is already experiencing devastation of COVID-19 in public health: more than 17 million of cases on July 31, 2020 in more than 200 countries, and almost 670 thousand of deaths, according to World Health Organization (WHO).

A pandemic of these proportions tends to have negative effects in several areas, and regarding the real economy, the impacts were no less dramatic. According to Goodell (2020), the main concerns arise from rising costs for health systems, loss of job productivity, social distance that disrupts economic activity, depressed tourism and impacts on foreign direct investment. Some of these phenomena are idiosyncratic of this current pandemic, and they seem to be able of generating uncertainties that are impacting the global financial markets very strongly. An evidence that supports this argument is reported in Baker et al. (2020). They propose using text-based methods to examine US stock market returns dating back to 1900 and volatility dating back to 1985 and they conclude that no infectious disease, including the Spanish Flu, has ever impacted the stock market as forcefully as COVID-19. They also show that in the period from February 24 to March 24, 2020, there were 22 trading days and 18 market jumps (daily move greater than 2.5 percent, up or down) – more than any other period in history with the same number of trading days.

In sum, they claim that COVID-19 related news can drive stock market prices in US in a dramatic form. According to Matos, Costa, and da Silva (2020), S&P 500 had a cumulative drop higher than 30%, considering only the period from February to April 2020, and US sectoral indices also recorded high and heterogeneous drawdowns, ranging from 23% (S&P 500 Consumer Staples) to 57% (S&P 500 Energy), for instance.

A natural and expected consequence is that COVID-19 has already a relevant, rapidly growing economics and finance literature, albeit focused primarily on developed countries. This literature concerns multiples aspects ranging from health and labor economics to growth and behavioral responses.

[1] Matos gratefully acknowledges financial support from CNPq-Brazil. For helpful comments on earlier drafts, we thank seminar participants at various institutions and conferences and the anonymous referees for relevant remarks. All errors are ours. Email adresses: antoniocostabr@gmail.com (A. Costa), cristiano.dacostadasilva@hotmail.com (C. da Silva) and paulomatos@caen.ufc.br (P. Matos).

Ashraf (2020) analyze the stock market response to COVID-19 pandemic using a panel data of 64 countries with observation from January 22, 2020 to April 17, 2020. He uses growth on daily COVID-19 confirmed cases and deaths as explanatory variables and finds that stock market returns declined as the number of confirmed cases increased and that stock markets reacted more proactively to the growth in number of confirmed cases as compared to the growth in number of deaths. His results also suggest negative stock market reaction varies over time depending on the stage of outbreak.

Wu et al. (2020) use the coherence wavelet method and the wavelet-based Granger causality tests applied to US stock market. 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.

More recently, Matos, Costa, and da Silva (2020) propose assessing 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. They 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. They also report that 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. Concerning the sectoral contagion, they find that the energy sector seems to be the first to react to the pandemic, and that the 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.

In this context, we are aligned to Matos, Costa, and da Silva (2020), however our aim is to add to this debate applied to emerging markets with high numbers of cases and deaths. More specifically, we intend to answer how the Brazilian stock market has responded to COVID-19, based on the cases or deaths in the most affected countries, in the Chinese province of Hubei, in China itself, and in the world. The reason for choosing Brazil is simple: Brazil is a record holder among the emerging ones. In the period recorded by WHO, until July 31, 2020, the three countries where there was a greater number of cases were: United States (4,388,566), Brazil (2,552,265) and India (1,638,870). In the same time period, US (150,054), Brazil (90,134) and United Kingdom (45,991) registered the highest number of deaths.

Our purpose provides an extra motivation to the use of wavelet framework once it is suitable to track time varying relations. Also, we differentiate ourselves in using, in addition to local cases and deaths series for a given country, the series of selected foreign localities.

In our first empirical exercise, we follow Aguiar-Conraria et al. (2018) by using partial coherences, partial phase-differences, and partial gains to better understand the conditional relation between the stock market returns and COVID-19 series and, if any, which lead-lag conditions can be drawn. We also propose studying the presence of contagion and the pass-through – based on Granger causality – of crises among Brazilian economic sectors. As for wavelets, they are considered as a powerful mathematical tool for signal processing which can provide more insights to co-movement among international stock markets via a decomposition of the time series into their time scale component (Aloui and Hkiri, 2014). Similarly, wavelets can be used to study sector indices co-movement in a specific country, one of the objectives of the present work related to sectoral contagion (almost exactly) as defined in Forbes and Rigobon (2002). So, for contagion, we use the distance metric discussed in Aguiar-Conraria and Soares (2011), and Value at Risk ratio analysis following Rua and Nunes (2009), both in time frequency domain. The data covers from January 22 to July 31, 2020 the longest period possible given limitations inherent to the pandemic. The data are provided by Investing.com and Center for Systems Science and Engineering (CSSE) at Johns Hopkins University (JHU).

The layout of the remaining of this paper is the following: Section 2 outlines the methodology, while Section 3 describes the data and presents the results. Section 4 offers some concluding remarks.

2. Methodology

The wavelet transforms originally explored empirically by Grossmann and Morlet (1984) are widely applied in some areas, as physics and medicine and they have also been used in economics, since pioneer works of Ramsey and Zang (1996 and 1997) and Ramsey and Lampart (1998) and in finance, as Rua and Nunes (2009), and Reboredo and Rivera-Castro (2014). 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 (τ, 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 l_x^k and 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 partial wavelet coherency between y (index) and x (COVID-19) after controlling for $\boldsymbol{z}$ is given by

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

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

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

For a self-contained review on continuous wavelet transform applications see Aguiar-Conraria and Soares (2014).

We also test causality between the COVID-19 metrics and the Brazilian stock index, IBOV, 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.

3. Data and empirical results

3.1 Data

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 22 to July 31, 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). Thus, after transformations, and considering that we used the first lag of COVID-19 variables, we start actual analysis on January 31, 2020.

Concerning the financial variables, we use daily returns on the main broad Brazilian stock index, Ibovespa (IBOV), and on its 7 sector indices: Basic Materials (IMAT), Electrical Energy (IEE), Industrials (INDX), Consumption (ICON), Financials (IFNC), Public Utilities (UTIL), and Real State (IMOB). All those indices are

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

formed by the most representative and traded stocks on Brasil Bolsa Balcão (B3), are total return indices, are rebalanced four-monthly, and except for IEE, are weighted by market cap. IEE is an equally weighted index.

Moreover, again except for IEE, all the sector indices used include a range of economic activities. Indeed, according to B3 definition, Basic Materials (IMAT) includes wood and paper, mining, chemistry, and metallurgy sectors. Industrials (INDX) covers basic materials, industrial goods, cyclical consumption, non-cyclical consumption, information technology and health. Consumption (ICON) is comprised of cyclical and non-cyclical consumption, and health. Financials (IFNC) span companies within the financial intermediaries, financial services miscellaneous, pension and insurance businesses. Public Utilities (UTIL) includes electrical energy, water and sanitation and gas. Real State (IMOB) are restricted to real estate exploration and civil construction companies.

Despite being a very informative database, there are few sector studies in Brazil. It is therefore relevant to mention some of these contributions. Righi, Ceretta and Silveira (2012) present a performance comparison of the Brazilian sector stock indices using daily returns from January 2007 to April 2010 concluding that, according to selected financial metrics, Electrical Energy sector presented the best overall performance.

Using daily data from January 1995 to August 2011, Almeida, Frascaroli and Cunha (2013) study how firm level stocks prices in Brazil and the Brazilian and US broad stock market indices interact to capture spillover effects. They conclude that a distress in the Brazilian broad market generated larger effects as compared to one in the international stock market. Using a contagion matrix, they also suggest that contagion relations in the firm level in Brazil stress the importance of sector analysis to risk management. Righi, Ceretta and Silveira (2014) study the presence of linear and non-linear cointegration among sector indices in Brazil using data from January 2008 to December 2010. They found that only Electrical Energy – Financials and Consumption – Financials showed presence of long-term relations. Matos, Sampaio and Castro (2017) statistically identify series of expectations of macroeconomic variables relevant to the GARCH model of Brazilian sector indices volatility while using CAPM for the mean model. These results emphasize the presence of non-stationarity in the Brazilian stock market, one that can be dealt with using the wavelet approach.

In order to add to this literature, in our empirical exercise we control for a specific set of instruments, namely the first and second lags of IBOV and S&P Global 1200 (S&P1200), the former index account for local stock market conditions while the later controls for global stock market. S&P1200 is composed of S&P500 (US), S&P Europe 350, S&P TOPIX 150 (Japan), S&P/TSX 60 (Canada), S&P/ASX All Australian 50, S&P Asia 50 and S&P Latin America 40 capturing approximately 70% of global market capitalization. The data sources for financial variables are Investing.com and S&P Down Jones Indices website.

Figure 1.a suggests a pattern of convergence during the pandemic, giving the first hint of contagion among sectors. We highlight that only the Basic Materials (IMAT) had cumulative gains in the period. The drawdowns recorded were between 34,0% (Electrical Energy - IEE) and 54.4% (Real State – IMOB).

The 7 days moving average of covid-19 deaths in the selected locations (Figure 1.b) seem to show that the worst is now behind for most countries. The record high world numbers have been reached in mid-April and, since that, most countries have reached plateaus or show decaying number of deaths. We highlight that Brazil took the longest among the selected locations to begin a plateau (only on beginning of June) and that the US was the only locality were some relevant degree of recrudescence of deaths was observed in July.

As for the moving average of cases (Figure 1.c) in the world, we have had a local maximum in the end of March and, after a little decrease, a slowly but surely increase in the numbers have been observed. Here we note that US had a very similar behavior to the world, that Brazil did not visually reached a maximum up to the end of July and that most of the other locations depicted here seem to have decreasing numbers for a while and then experienced increasing numbers by the end of June.

It is notetaking, and relevant to the present study, the fact that we have a apparent different behavior in series of deaths and cases: deaths have declined in a more monotonic from the record highs, cases have somewhat had a slower way down with more visible episodes of recrudescence. This pattern, probably partially driven by availability of testing, is more evident for world, European countries, and China, while in Brazil and US we also can see that the number of deaths has decreased (or increased) less than the number of cases. This disparity of patterns suggests that investors may have had heterogeneous perceptions of the deaths and cases data along different moments of the pandemic, which highlight the importance of the wavelet methods used in the present paper.

Summary statistics of the 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 returns on IBOV and the COVID-19 series. As can be seen there, most dissimilarities are significant at 10% (except for deaths in France and Brazil and cases in China, Hubei, and France). Both cases and deaths in US are significant at 1% as is cases in Italy. Deaths in Italy and UK, and cases in world, UK and Brazil are significant at 5%. This means that the IBOV and the COVID-19 series have similar content when compared in the time-frequency plain, suggesting, in a very preliminary stage, that the selected variables may in fact have some good information about each other.

3.2 COVID-19 effect on Brazilian Stock Market index (IBOV)

Our first empirical exercise uses wavelet partial coherences, partial phase-differences and partial gains aiming to show how COVID-19 deaths and cases in different localities are related to returns on Brazilian stock index (IBOV) one day ahead.

We report the results for the most relevant series on Figure 2. There, the partial wavelet coherencies are plotted as 2-dimensional heat-maps, where warmer colors represent higher coherences (unity coherence is depicted in red, and nearly null coherences in blue). The cone of influence, region subject to edge effects, 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). To prevent edge effects, each analysis begins when the related COVID-19 series presented the first non-null data. Also, for Hubei cases and deaths (not Shown) and for China deaths (Figure 2.b) the analysis ends when a zero-reported number have occurred the first time.

Regarding statistical significance, we follow Aguiar-Conraria et al. (2018) using Monte Carlo Simulations to construct significance contours for the partial coherences. We use red noise as null hypotheses, meaning that we fit a AR(1) model to each of the series and get surrogates by drawing errors from a Gaussian distribution with a variance equal to that of the residue. Limits of confidence interval for mean phase-differences are derived following Zar (1996) and shown as dashed black lines in the phase-difference diagram.

How to appropriately obtain confidence intervals for the gain is a question which still remains open; for this reason, one should complement the analysis of the gain by inspecting coherency, and only focus on the regions whose corresponding coherency is statistically significant (Aguiar-Conraria et al, 2018).

Considering all 16 possibilities involving IBOV and cases or deaths in each of the chosen locations, we plot and analyze only the figures and the diagrams with a higher incidence of regions with strong partial coherency: deaths in US, China, Italy, and Brazil and cases in US, Italy, France and Brazil.

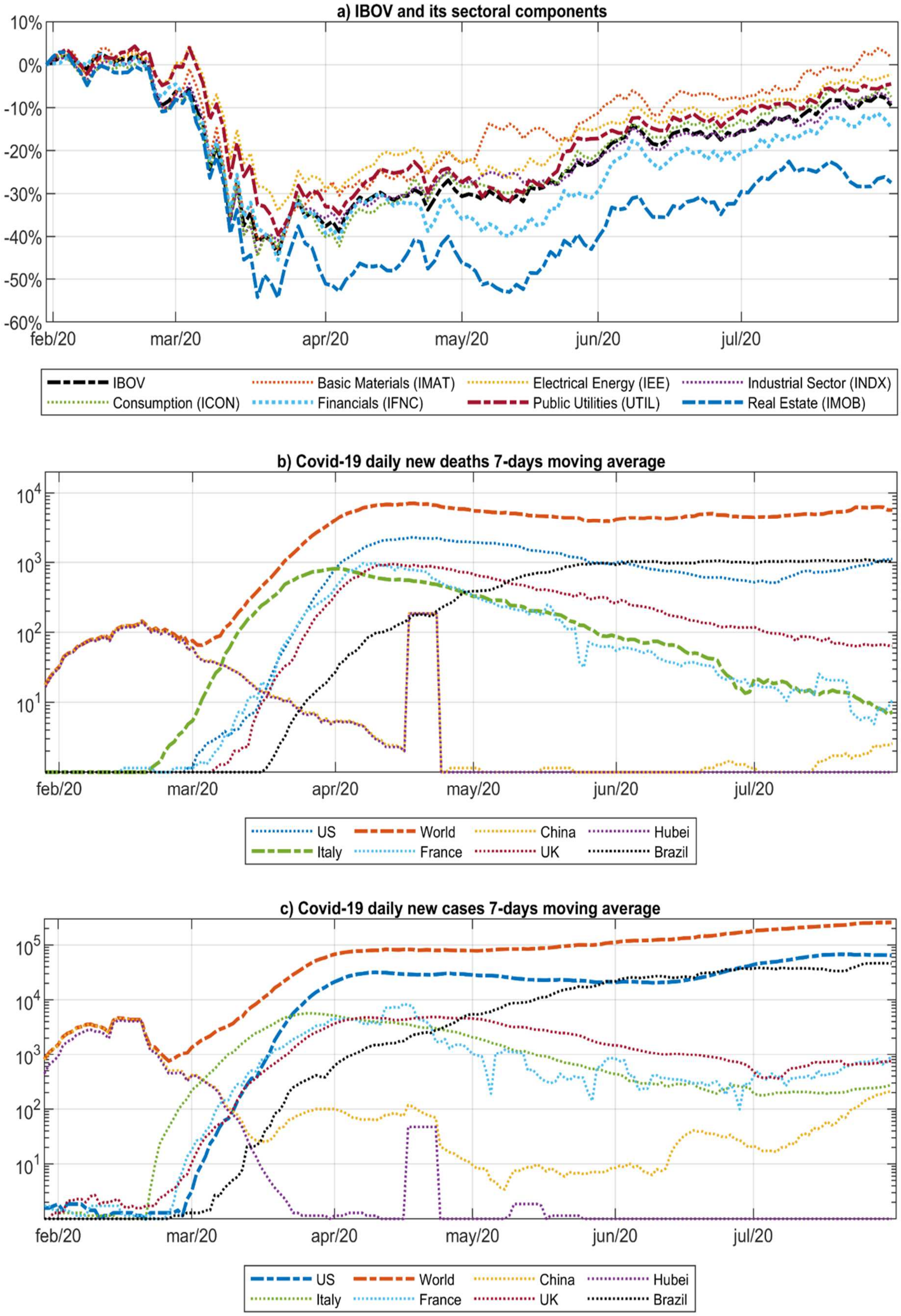

Figure 1: Cumulative return on Brazilian stock market, IBOV, and its sector indices, and COVID-19 numbers worldwide. [a]

Notes: [a] Data from January 29 to July 31, 2020. Source: Investing.com and Johns Hopkins Corona Virus Research Center.

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

		US	World	China	Hubei	Italy	France	UK	Brazil	US	World	China	Hubei	Italy	France	UK	Brazil
Panel A. Dissimilarities																	
IBOV		.33***	.47*	.31*	.32*	.44**	.67	.42**	.59	.33***	.39**	.67	.49	.36***	.55	.44**	.39**
Panel B. Granger causalities																	
IBOV mean	COVID → Index	(.84)	(.91)	(.64)	(.87)	(.12)	(.38)	(.11)	(.00)***	(.50)	(.59)	(.03)**	(.20)	(.18)	(.63)	(.14)	(.84)
	Index → COVID	(.25)	(.77)	(.44)	(.40)	(.80)	(.63)	(.28)	(.09)*	(.06)*	(.40)	(.08)*	(.23)	(.01)**	(.25)	(.24)	(.01)**
IBOV quantil 0.10	COVID → Index	(.20)	(.16)	(.11)	(.99)	(.19)	(.19)	(.01)**	(.02)**	(.16)	(.16)	(.16)	(.08)*	(.27)	(.21)	(.16)	(.19)
	Index → COVID	(.01)**	(.16)	(.15)	(.53)	(.51)	(.01)**	(.09)*	(.03)**	(.01)**	(.01)**	(.01)**	(.08)*	(.01)**	(.39)	(.08)*	(.01)**
IBOV quantil 0.90	COVID → Index	(.03)**	(.02)**	(.04)**	(.05)**	(.03)**	(.03)**	(.03)**	(.03)**	(.03)**	(.02)**	(.02)**	(.08)*	(.03)**	(.02)**	(.02)**	(.03)**
	Index → COVID	(.31)	(.02)**	(.15)	(.62)	(.09)*	(.69)	(.47)	(.37)	(.06)*	(.07)*	(.43)	(.08)*	(.99)	(.01)**	(.06)*	(.04)**
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.)		4.2%	3.3%	-0.7%	-1.2%	1.2%	0.9%	2.2%	3.9%	5.9%	3.5%	0.0%	-2.8%	1.4%	3.5%	3.8%	5.4%
St. dev. (Daily Log Growth - 7 Days Mov. Aver.)		10.8%	8.2%	9.5%	8.4%	11.8%	23.0%	10.2%	7.6%	14.5%	10.4%	16.3%	16.4%	9.6%	34.0%	13.0%	9.7%

Notes: [a] Data from January 31 to July 31, 2020. [b] Dissimilarities between IBOV 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 parenthesis. Source: Investing.com and Johns Hopkins Corona Virus Research Center.

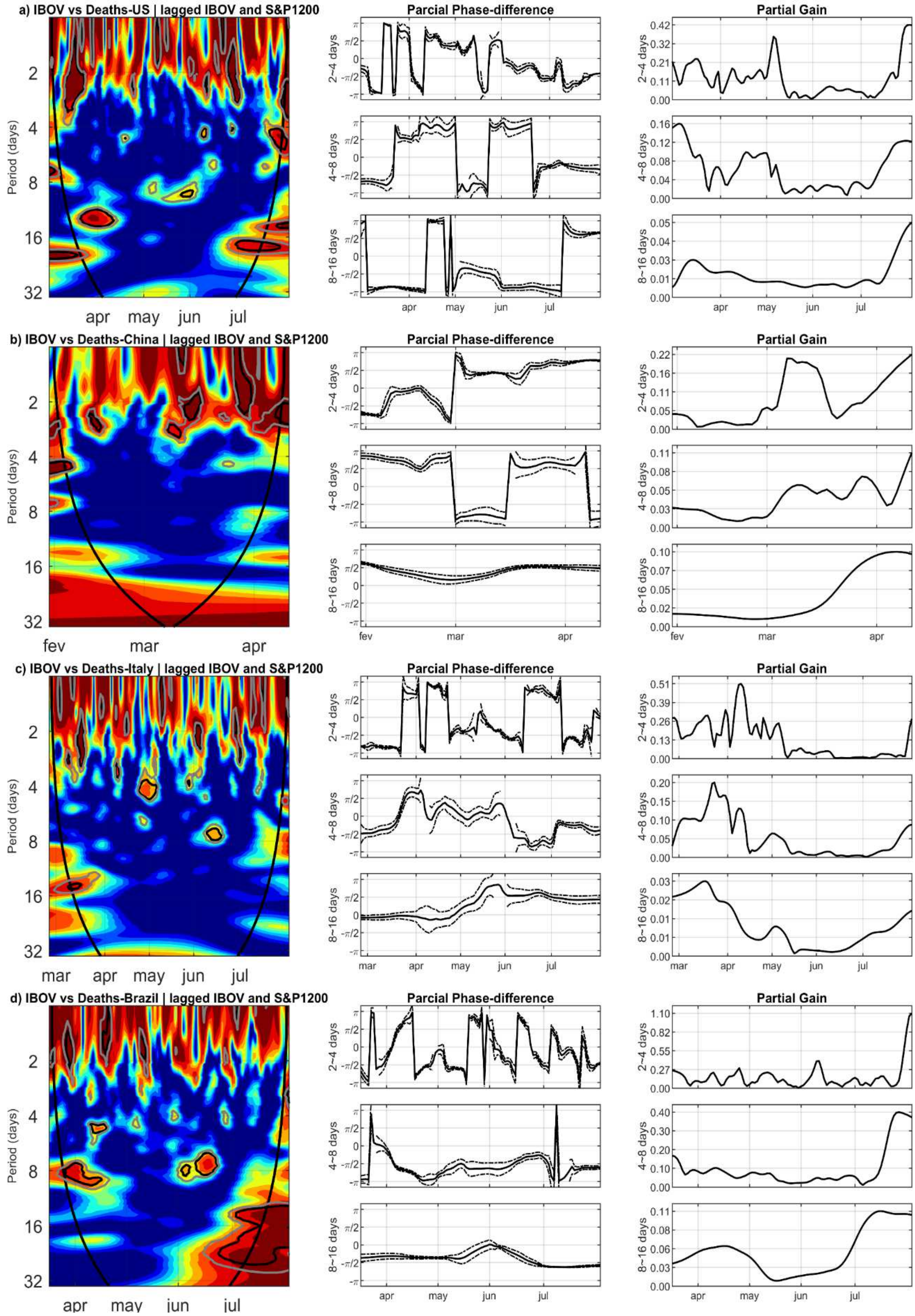

Figure 2: Partial wavelet framework of IBOV vs COVID-19 controlled by first and second lag of IBOV and S&P Global 1200.

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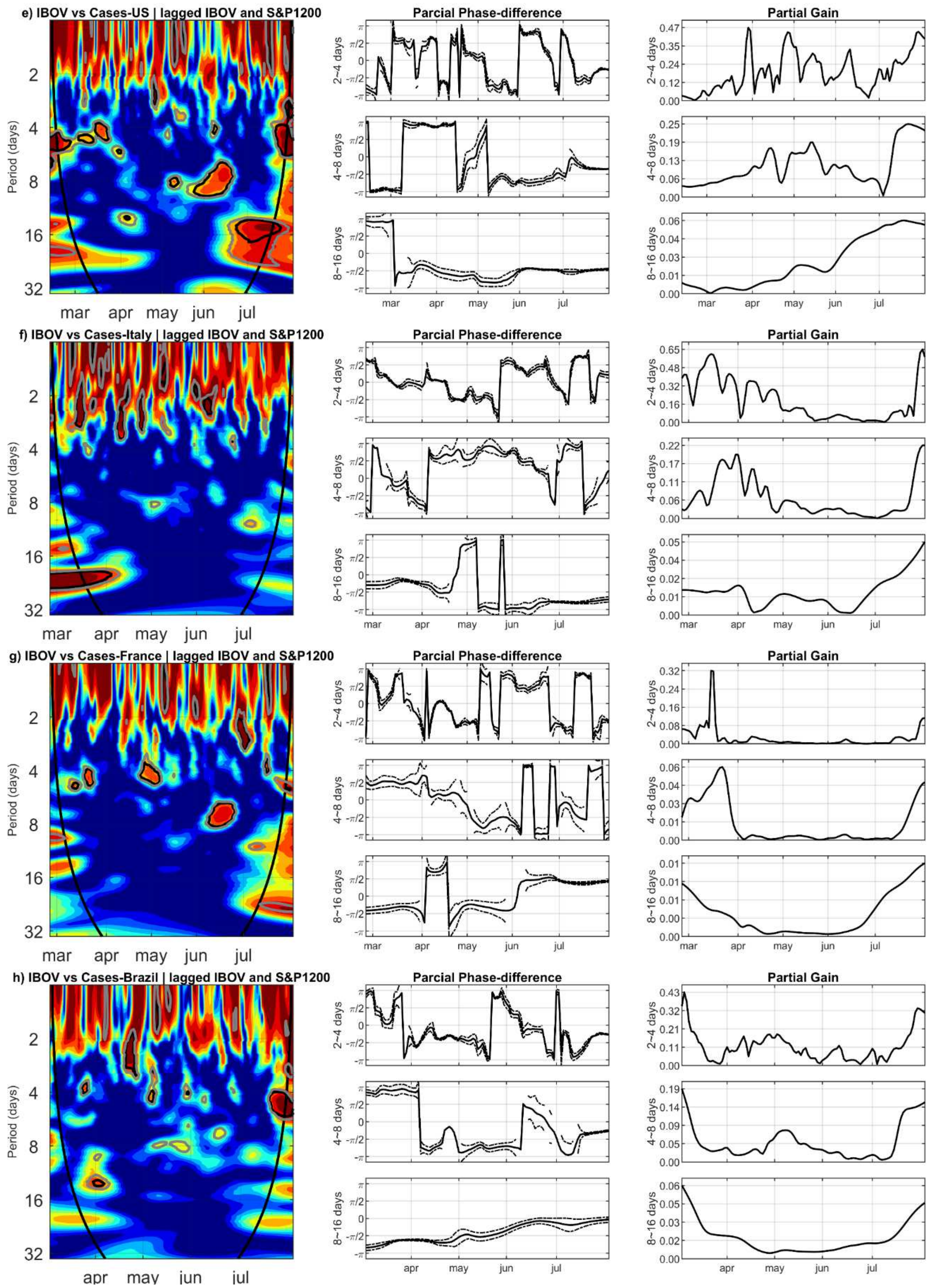

Figure 2: Partial wavelet framework of IBOV vs COVID-19 controlled by first and second lag of IBOV and S&P Global 1200.

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 31 to July 31, 2020. Source: Investing.com and Johns Hopkins Corona Virus Research Center.

Taking US deaths, reported in Figure 2.a, looking at the high frequencies (band of 2~4 days), we find a first very important strong and significant partial coherence region covering most of second half of March. In the corresponding time-frequency region the partial phase-difference shows signs of instability, assuming values either near -π or near π, being the latter prevalent, meaning that for the entire time span analyzed IBOV and US deaths experienced an anti-phase relation and for the most part US deaths lead the Brazilian stock market index. Put in another way, returns on IBOV responded negatively (positively) to the news of increase (decrease) of deaths in the US occurred in the day before. During this time, we can also observe the formation of a local maximum in the partial gain function, at about 22%. This period happens to match the most grueling time in the entire COVID-19 pandemic for the stock market (In Brazil and elsewhere), when bottoms were being reached, after what the partial recovery has been observed.

Noteworthy is the presence of spots of high and significant partial coherence around the same time-frequency region (second half of march, 2~4 days band) for the remaining deaths and cases series, with slightly bigger significant regions registered on the deaths heatmaps and a highlight to the US cases. This recurrence of high coherence spots for series of deaths of various localities and for US cases in this particular critical moment of time and with a concentration in high frequency bands are aligned with Matos, Costa, and da Silva (2020) for the American stock market. The main suggestion may be that in the most critical moment of COVID-19 pandemic for the stock market, the investors in the Brazilian market (as well as in the American) were very aware of the deaths counts not only locally and took actions in the smaller horizons of time available.

These findings also highlight a slight prevalence in this critical point at the time-frequency plane for US and Brazil, of deaths data over cases data in the perception of investors. We understand that one plausible explanation may be the desperate try of market participants of getting the most reliable information possible, which happens to be the one on deaths for a series of reasons as underreporting either because of asymptomatic spread or for testing limitations. Also, one can arguably state that the most pronounced effects on economic activity are more directly linked to the cases that develop to more than mild symptoms partially translating in deaths.

As for Ashraf (2020) conclusion that COVID-19 cases data are the ones to look at, our exercise brings a new perspective because we are looking at foreign series in addition to local series and because we are using time and frequency domain. That said, expanding the observation to significant areas over the entire plain and to all pair of series of COVID-19 under consideration, we do not see a clear winner among the deaths and cases series. We, however, highlight that the relevance of each data type show heterogeneity in time and frequency.

Progressing in the analysis of the first exercise, once again with US deaths (Figure 2.a), we observe yet in the 2~4 days frequency band a high and significant spot around the end of June. There the phase-difference is little less than -π/2 (antiphase and IBOV leads). The gain is about 5%. Figure 1.b shows this period match the beginning of a somewhat relevant recrudescence in deaths in US soil which may have prompted attention of investors. US deaths also shows significant spots over the highest frequency (period < 2 days), towards the end of sample over the 4~8 days band and at three different moments in time in the 8~16 days band. For brevity we are not going to analyze them separately.

For China deaths (Figure 2.b), besides the critical region already analyzed, we highlight a small spot of significant partial coherence in mid-February, with a phase-difference of little less than zero (deaths in China leads in phase) and a very small gain of less than 1%. At this point in time the world deaths are almost all concentrated in China, but it is already possible to see some cases in Europe, what may have alerted the most risk averse individuals.

As For Italy deaths (Figure 2.c), the biggest spots of significant partial coherence are located in the end of April (phase difference of zero, in phase, move together) and mid-June (phase difference between -π/2 and -π, IBOV leads, out of phase movement) both in the 4~8 band.

Analyzing the Brazilian deaths (Figure 2.d) series, the most relevant points not yet discussed is a big significant area on the longest terms (8~16 days and over 16 days periods) toward the end of sample with phase-difference in the third quadrant (IBOV lead in antiphase) and a gain of 11%.

For US cases (Figure 2.e), by far the cases series with the most significant area on the partial coherence heatmap, we highlight the occurrence of a big significant area spanning both 2~4 and 4~8 days frequency bands and beginning at the second half of May lasting approximately one month. In both frequency bands the movement is led by IBOV in an antiphasic way. This first noteworthy region is followed in time by a cluster even bigger of high and significant partial coherence in lower frequencies. These two regions together occur, as reported before on the analysis of the US death series (Figure 2.a), during a noticeable recrudescence of deaths in US, what may have reflected in an increase of awareness for US of deaths and cases.

Italy cases (Figure 2.f) show a series of spots on short cycles and a big coherence area in the beginning of sample and the slowest frequencies. France cases (Figure 2.g) have three good sized spots of significant partial coherence concentrated on 4~8 days frequency bands. And finally, Brazil cases (Figure 2.h) shows the biggest spots in short and midterm frequency bands during second half of April and towards the end of the sample, respectively.

Also, in the Table 1 (Panel B), we report the *p-values* of the test for Granger-causality in mean (Granger, 1969), and in quantiles (Troster, 2018) to considers the pattern of dependence in the conditional tails of the distribution. For the center of the distribution, there is no predictability between COVID-19 cases and IBOV index, except for the relationship between Brazil cases and IBOV, where we found bi-causality. The IBOV index leads changes in US, Italy and Brazil deaths, and we find bi-causality between the Index and China deaths. So, for the center of the distribution the Granger-causality analysis indicates that the COVID-19 outbreak has a low effect on the Brazil stock market. However, the Granger-causality in mean possibly ignores the movements in the investors' perception of risk during different paths of the pandemic.

For the upper extreme tail of the conditional distribution ($\tau = 0.90$) we highlight that all COVID-19 measures have high degree of predictability on the stock market fluctuations while the IBOV Index is causing only the World cases and US, World, Hubei, France, Italy and Brazil deaths. This result means that the COVID-19 large spread ($\tau = 0.90$) motivated great uncertainty at the Brazilian stock market, which in turn caused the inability of the investor to predict the path of the COVID-19 pandemic same at short-term.

The picture is inverted at the first decile of conditional distribution ($\tau = 0.10$) where the fluctuations on the stock market has predictive power over eleven COVID-19 metrics and it is predicted only by UK cases, Brazil cases and Hubei deaths. Thereby it is reported that market returns had a good performance to predict the drop in the virus spread.

3.3 Brazilian sectorial contagion and pass-through

Given the dramatic turmoil experienced in the stock markets during COVID-19 pandemic, sometimes of unprecedented proportions, as shown in Baker et al. (2020), and the asymmetric effects on markets highlighted, for example, in Mazur, Dang and Vega (2020) two additional research questions seem natural. First, can we verify the presence of contagion among sectors in a specific country during COVID-19 pandemic period? Second, what is the crisis pass-through among the economic sectors?

Thus, our second empirical exercise shed some light on these questions for one of the most economically relevant emergent markets: the Brazilian.

Specifically, we propose evaluating the sectoral contagion, series, and crisis pass-through among IBOV sector indices during the pandemic spread using both wavelets and Granger causality-based methods.

Initially we evaluate the evidence of sectorial contagion, defined, in line with Forbes and Rigobon (2002)[3], as the increase of cross-sector linkages among the returns on IBOV sector indices during the first semester of 2020 as compared to the last semester of 2019. This is performed first using the wavelet spectrum distance metric in time and frequency - dissimilarity - and reported in Table 2 (Panel D).

Regarding the distance metric, there was a general decrease during COVID-19 pandemic with only 3 (two by less than 2%) out of 21 pairs of sectors registering any increase in dissimilarity. The average relative reduction in dissimilarity was of 12.1%.

The maximum decrease in dissimilarity, with magnitude of 27.2%, was computed to a pair of sectors heavily regulated by government: Public Utilities (UTIL) – Electrical Energy (IEE). This decrease indicates that in 2020 the time and frequency content of the returns on these sector indices were much more alike, suggesting an increase in cross-sector linkages and therefore contagion. The maximum increase in dissimilarity, 10.2%, was relates to the pair comprised of the best and worst performing sectors during pandemic: Basic Materials (IMAT) - Real State (IMOB) (see Table 2, Panel A for summary statistics of the sector indices). This is a very intuitive result once these indices have arguably experienced opposite behavior during pandemic. Also, one can see that among all sectors, only Basic Materials (IMAT), the best performing index, have a smaller number of significant dissimilarities in 2020 as compared to 2019.

Overall, we understand that the results on dissimilarities strongly suggests the presence of contagion among the Brazilian sectors during COVID-19 pandemic.

To further investigate the contagion in Brazil economic sectors, we follow Rua and Nunes (2009) performing a wavelet-based Value at Risk (VaR) exercise, reported on Figure 3. VaR is a well-established risk metric, representing the maximum loss to be expected of a portfolio in a period with a certain confidence level. The VaR of a portfolio in the 1- α confidence level can be defined in the following manner:

$$VaR(\alpha) = Io\Phi^{-1}(1-\alpha)\sigma_p \tag{7}$$

Where Io represents the initial investment, $\Phi(.)$ the cumulative distribution function of the standard normal, and σ_p the portfolio volatility. Assuming a portfolio with n assets, σ_p^2 can be computed as follows:

$$\sigma_p^2 = \sum_{i=1}^{n} w_i^2\sigma_i^2 + \sum_{i=1}^{n}\sum_{j=1,j\neq i}^{n} w_i w_j Cov(r_i, r_j) \tag{8}$$

In (8) w_i, σ_i, and r_i represents the weight of asset i in the portfolio, the asset i volatility and its returns, respectively. To compute the VaR in time frequency, we use the wavelet-based analog measures of variance and covariance in (8).

As one can see, the portfolio variance can be decomposed in two factors: individual assets variance and the covariance (co-movement) of pairs of assets. Thus, the ratio between the volatility of the portfolio with and without assuming co-movement brings information about how much linkage there is among the assets comprising the portfolio. Put in another way, analyzing how this ratio evolve in the time frequency plain can show if there is evidence of contagion (increase in linkage) among the components of the portfolio.

[3] Forbes and Rigobon (2002) define contagion as a significant increase in cross-market linkages after a shock to an individual country (or group of countries). In this work we look at a sectoral contagion, thus defining contagion as the increase of cross-sector linkages in one country (or a group of countries) affected by a shock.

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

Panel A: Summary statistics of Brazil sector indices

Statistics	IMAT	IEE	INDX	ICON	IFNC	UTIL	IMOB
Cumulative return	1.66%	-2.28%	-8.91%	-7.50%	-14.70%	-4.48%	-27.47%
Standard deviation	3.75%	2.85%	3.56%	3.84%	3.91%	3.40%	5.02%
Market beta	0.89	0.69	0.89	0.98	1.00	0.83	1.21
Drawdown	42.84%	34.00%	44.35%	44.71%	45.56%	39.52%	54.36%

Panel B: Dissimilarities and Granger causality, respectively, between IBOV and Brazil sector indices

Indices		IMAT	IEE	INDX	ICON	IFNC	UTIL	IMOB
IBOV		.34**	.28***	.25***	.25***	.20***	.25***	.29***
IBOV	Sector index → Index	0.14	**0.01**	0.28	0.54	0.17	0.11	0.44
IBOV	Index → Sector index	**0.00**	**0.02**	**0.02**	**0.02**	**0.00**	**0.01**	0.15

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

Indices	IMAT	IEE	INDX	ICON	IFNC	UTIL	IMOB
Basic Materials (IMAT)		0.95	0.72	0.30	0.89	0.78	0.53
Bovespa Electrical Energy (IEE)	0.31		**0.01**	**0.03**	**0.06**	**0.09**	**0.00**
Bovespa Industrial Sector (INDX)	0.43	0.61		0.31	0.52	0.38	0.47
Consumption (ICON)	0.99	0.93	0.45		0.62	0.82	0.74
Financials (IFNC)	0.50	0.21	0.57	0.22		0.19	0.29
Public Utilities (UTIL)	0.41	0.23	**0.02**	**0.05**	0.19		**0.01**
Real Estate (IMOB)	0.21	0.30	0.37	0.18	0.53	0.27	

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

Indices	IMAT	IEE	INDX	ICON	IFNC	UTIL	IMOB
Basic Materials (IMAT)	-	.49	.36**	.43	.41*	.49	.43
Bovespa Electrical Energy (IEE)	.39	-	.44	.38**	.35**	.15***	.36**
Bovespa Industrial Sector (INDX)	.26***	.35**	-	.28***	.39*	.43	.43
Consumption (ICON)	.44	.34**	.28***	-	.37**	.37**	.32**
Financials (IFNC)	.41	.30***	.37*	.36*	-	.33**	.34**
Public Utilities (UTIL)	.41	.09***	.35**	.31***	.26***	-	.36**
Real Estate (IMOB)	.47	.33**	.40	.30***	.28***	.27***	-

Notes: [a] Panel D uses data from July to December, 2019 and from January to June, 2020. The remaining data is from January 22 to July 31, 2020. [b] Dissimilarities between IBOV 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.

Besides, the mentioned volatility ratio is identically equal to the ratio of VaR with and without assuming co-movement. Thus, a higher than one value means that the co-movement among the assets comprising the portfolio is increasing its risk.

The Figure 3 shows the VaR ratio test performed, considering a portfolio formed by all 7 Brazilian sector indices under consideration at this paper[4]. Qualitatively, it is noteworthy the region of highest ratio clustered

[4] We also perform this analysis with all pair of sector indices individually. The conclusions do not change qualitatively, and the figures can be provided upon request.

from the first days of February to the end of Mach, 2020, the most difficult period for the stock market, and practically crossing all the frequencies. Also, one can see that 2020 shows overall much warmer colors in comparison to 2019, reflecting a higher mean ratio, and, thus, increased linkages.

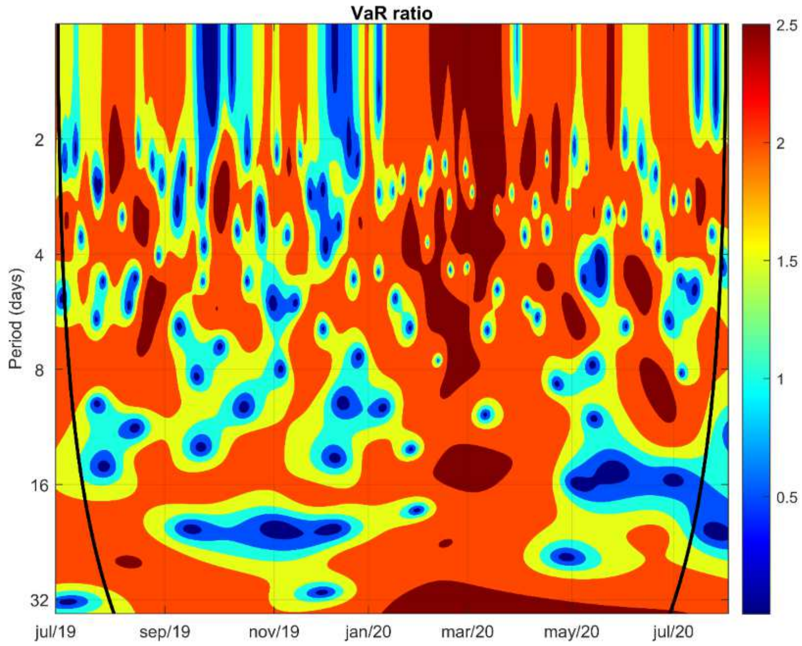

Figure 3: Ratio between the VaR of an equally weighted portfolio of Brazil sector indices with and without co-movement.

Numerically, the mean VaR ratio from July to December 2019 was 1.76, from January to June 2020 was 2.13 (increase of 21.0%). From February to April 2020, it was of 2.32 (increase of 31.8%).

Overall, these results reinforce the evidence of presence of contagion in between the Brazilian sectors during COVID-19 pandemic. Regarding the pass-through in the Brazilian economy, we perform Granger causality tests based on VAR among the sector indices, conditional to the two first lags of IBOV and S&P Global 1200. The p-Values of the tests are reported on Table 2 (Panel C).

We highlight predictive power of the two heavily regulated sectors. Electrical Energy (IEE) Granger causes Real State (IMOB) with 1% significance level, Industrials (INDX) and Consumption (ICON) with 5%, and Financials (IFNC) and Public Utilities (Util) at 10%. Public Utilities (UTIL) Granger causes Industrials (INDX), Consumption (ICON) and Real State (IMOB) all with a 5% significance level.

5. Conclusion

We fill the gap of the COVID-19 literature by studying the conditional relations 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 Brazilian broad stock market index, IBOV, from January 22 to July 31, 2020.

On this front, we highlight that our findings support the presence of significant conditional relations between international COVID-19 numbers and the Brazilian stock market. Particularly, we see a recurrent presence of significant relations in between the COVID-19 series and the IBOV in the most critical moment of the pandemic so far for the stock markets, namely the end of March 2020. These relations seem to be slightly more pronounced for death's series, although the US cases series seems to be of relevance.

Nevertheless, overall, considering the heterogeneity of relations in time and frequency, it is not clear, in the Brazilian case and considering the entire time frequency plane which set of data have been more relevant, thus we could neither confirm nor reject the conclusions of Ashraf (2020) for the Brazilian case.

Regarding the contagion, our studies on wavelet-based distance metrics and VaR ratio strongly support the presence of contagion, as defined by the increase in linkages between sectors after a shock, between the Brazilian sectors across all frequencies during COVID-19 pandemics. This result speaks loudly to the investor and portfolio managers interested in benefits of diversification that may vanish in such a critical moment.

Moreover, our Granger causality exercise findings support extraordinarily predictive power of heavily regulated sectors in the Brazilian markets, suggesting their strategic role for the policymakers.

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