Since January 2020 Elsevier has created a COVID-19 resource centre with free information in English and Mandarin on the novel coronavirus COVID-19. The COVID-19 resource centre is hosted on Elsevier Connect, the company's public news and information website.

Elsevier hereby grants permission to make all its COVID-19-related research that is available on the COVID-19 resource centre - including this research content - immediately available in PubMed Central and other publicly funded repositories, such as the WHO COVID database with rights for unrestricted research re-use and analyses in any form or by any means with acknowledgement of the original source. These permissions are granted for free by Elsevier for as long as the COVID-19 resource centre remains active.
The Brazilian financial market reaction to COVID-19: A wavelet analysis

Antonio Costa a,*, Cristiano da Silva b, Paulo Matos a

a CAEN Graduate School of Economics, Brazil
b UERN – Rio Grande do Norte State University, Brazil

ARTICLE INFO
JEL classification:
G12
C63
H12
O16
Keywords:
Brazilian stock market
COVID-19 impacts
Lead-lag conditional relationships
Time-frequency domain
Wavelets

ABSTRACT
We study the Brazilian stock market response to the COVID-19 pandemic. Considering the COVID-19 data from January 22, 2020, to August 31, 2021, and a daily dataset comprised of the Bovespa index - the main performance indicator of the stocks in the Brazilian capital market -, its sector components, and COVID-19 cases and deaths in the most affected countries, we employ the wavelet tools of partial coherences, partial phase differences, dissimilarities, and VaR ratio. We find significant partial coherence spots, decrease in dissimilarity, and increase in VaR ratio suggesting the Brazilian stock market responded forcefully to COVID-19 local and international data and that this response varies over time and frequencies being modulated by the local stage of outbreak. The results also suggest a higher response to deaths data and that both market wide response and the sector contagion are more evident on longer term frequencies.

1. Introduction
Since the end of 2019, a respiratory disease identified in the Chinese city of Wuhan has evolved into a truly global pandemic. About a year and eight months later, the worldwide community has experienced nothing short of a public health devastation caused by the Coronavirus disease 2019 (COVID-19): 217 million cases, 4.5 million deaths in nearly 200 countries, territories, or areas (hereafter countries) as of August 31, 2021. Also, according to the COVID-19 Weekly Epidemiological Update, Edition 55, published on August 31, 2021, by the World Health Organization (WHO), cases of the Alpha variant have been reported in 193 countries, the Beta variant is reported in 141 countries. Gamma and Delta variants cases are reported in 91 and 170 countries respectively. In terms of worldwide numbers, the American continent registers 39% of the cases and 47% of the deaths. The European continent is the second in both indicators.

Even after this generalized spread of the COVID-19, with three main waves of world deaths peaking in April 2020, January 2021, and April 2021, and despite the advancing in vaccinal coverage in many countries, the deaths data evolution from June 2021 to the last
week of August 2021 still inspire concerns.

The COVID-19 outbreak has had severe economic consequences across the globe, and it does not look like any country will last unaffected (Donth & Gustafsson, 2020). According to Goodell (2020), the main concerns stem from rising health systems costs, declining labor productivity, a social distancing that disrupts economic activity, sluggish tourism, and impacts on foreign direct investment. Some of these phenomena are idiosyncratic of this current pandemic and seem to be able to generate uncertainties that have a strong impact on global financial markets. In fact, the rapid spread of COVID-19 has had dramatic impacts on financial markets (Zhang et al., 2020).

As a natural consequence, COVID-19 has an already relevant, rapidly growing economics and financial impacts literature. This literature employs diversified methodological approach but is focused primarily on developed countries.

For instance, Baker et al. (2020), use text-based methods to examine the US stock market returns dating back to 1900 and volatility dating back to 1985, and conclude that no infectious disease, including the Spanish Flu, has ever impacted the stock market as forcefully as the 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, the authors claim that COVID-19 related news can drive stock market prices in US in a dramatic form.

Sharif et al. (2020) use the coherence wavelet method and the wavelet-based Granger causality tests applied to the 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 et al. (2021a), have assessed 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 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 is useful to tell the pass-through history of this recent health crises across the sectors of the US economy.

Ashraf (2020) analyzes the stock markets reactions to COVID-19 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.

Matos et al. (2021b) revisit the discussion on banking system contagion, performing a risk-based empirical analysis during the current pandemic period, considering daily returns on G7 banking sector indices from January 1, 2015, to December 31, 2019 (pre-pandemic), and from January 1, 2020, to October 16, 2020 (pandemic). Using a wavelet-based Value at Risk (VaR) ratio analysis, considering 21 possible pairwise combinations with the G7 financial indices, their findings suggest increased linkage between banking systems, that is, financial contagion. The greatest contagion is evident between the Italian and French banking systems, countries severely affected by COVID-19, while they find less evidence of contagion between Japan and Germany, countries least affected by the first wave of COVID-19.

Karamti and Belhassine (2021) analyze the connectedness between the COVID-19 pandemic and major financial markets within a wavelet framework which enables them to identify the differences between the short-term and longer-term markets’ reactions. In the short run, they find strong co-movements during the first and second waves of the pandemic. During the first wave, longer-term investors were driven by the belief of future pandemic demise, so it seems that they make use of time diversification that results in positive returns. Since US becomes the new coronavirus epicenter, they also find that the US COVID-19 fear spills over into the international markets.

In this context, we are conceptually and methodologically aligned to Matos et al. (2021a,b), and to Karamti and Belhassine (2021). More broadly, we add to the debate on COVID-19 financial market impacts literature. However, we intend to add to this literature by focusing on a highly relevant emerging market that has been severely affected by the pandemic.

More specifically, we intend to answer how the Brazilian stock market has responded to the waves of COVID-19, based on the conditional relation between COVID-19 cases or deaths - in the most affected countries, in the Chinese province of Hubei, in China itself, and in the world -, and the returns on the main performance indicator of the stocks in the Brazilian capital market, the Bovespa index. Furthermore, we study the potential financial contagion among the Brazilian sectors.

We add to the literature on COVID-19 induced financial markets impacts in three main forms. Initially regarding the scope of this study, we are the first, to our knowledge, to provide a comprehensive analysis on how COVID-19 numbers are related to the Brazilian stock market returns from early days of the pandemic through the end of August 2021. We are also the first to analyze sector contagion in Brazil in the same time frame.

Second, methodologically, we employ specific continuous wavelet transforms tools that have been underexplored in this literature with some practical advantages. For instance, we employ partial wavelets coherences with multiple control variables providing additional robustness compared to the usually employed unconditional wavelet coherence analysis. The wavelet based VaR ratio, and the dissimilarity metric used provide time-frequency measures of financial markets participants linkages intensity, being natural.

4 See the evolution of world deaths in Fig. 1 (Panel B).
candidates to analyze financial contagion as defined by Forbes and Rigobon (2002), with the advantage of allowing short-long run heterogeneity evaluation.

Third, also methodologically, considering the lack of uniformity on the literature as reported in Zhang et al. (2021), we are the first, to our knowledge, to propose employing the well-known-in-economics Harding and Pagan (2006) method to identify the COVID-19 world deaths waves and allow comparative analysis to target interesting sections of the pandemic.

There are many reasons as for why Brazil is a relevant case to be explored. For instance, the number of cases and deaths in a country may serve as a further stressor of local economy, and, consequently, contribute to spillovers to the financial markets. Thus, the Brazilian high incidence of COVID-19 contributes to its importance as a case to be studied. In fact, Brazil is a record holder among the emerging economies, from its first wave. To be specific, as of August 31, 2021, Brazil was the third country with the most cases (20.8 million), behind the United States (39.2 million) and India (32.8 million). Looking at the cumulative number of deaths, Brazil had 580.4 thousand, second to only the United States, which accumulated 640.2 thousand. Furthermore, Brazil is one of the largest economies, mostly among the emerging ones. Particularly, it is a highly relevant commodities exporter. Thus, Brazil arguably may play a key role to many countries recoveries as an input supplier once the crisis begins to fade, in a way that the Brazilian case should be of interest for a larger audience.

Once the Brazilian case importance is demonstrated, we provide an overview of employed data, main aspects of the two empirical exercises performed, and main findings.

Our entire time span is from April 30, 2018, to August 31, 2021, at a daily frequency. Following Akhtaruzzaman et al. (2021) and Costa et al. (2021), we have considered the COVID-19 period to begin on December 31, 2019 - the day cases of pneumonia detected in Wuhan, China, are first reported to the WHO. The pandemic period goes to the end of our sample, on August 31, 2021.

Concerning the variables used, the health dataset is comprised of series of deaths and cases of COVID-19 in the most affected countries by June 30, 2020: US, Brazil, United Kingdom, Italy, and France. We also use data from China and its Hubei Province to allow analysis of early stages pandemic impacts. World data is included for robustness. The COVID-19 data is available from January 22, 2020. Regarding the financial variables, we use daily returns on the main broad Brazilian stock index, the Bovespa Index (BVSP), 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).

As a preparation to the empirical exercises, following Zhang et al. (2021), we have considered that the pandemic waves are characterized by a sequence of sustained upward and downward trend periods in the COVID-19 data. We have then applied the Harding and Pagan (2006) method to the world death data and identified 4 COVID-19 waves: from January 22, 2020, to May 28, 2020, from May 29, 2020, to October 02, 2020, from October 03, 2020, to March 16, 2021, and from March 17, 2021, to July 2, 2021. These periods have been used to target sections of interest on the pandemic throughout the analysis performed.

In our first empirical exercise we aim to understand the conditional relation between the Brazilian stock market returns and COVID-19 series. Put differently, we use wavelet partial coherences, and partial phase-differences to show how COVID-19 deaths and cases in highly affected localities are related to returns on the Bovespa index. On this exercise, we control for a specific set of instruments, the 5 Brazilian risk factors published by the Brazilian Center for Research in Financial Economics at the University of São Paulo.

Among several results, a higher incidence of significant partial coherences areas indicates the most (least) relevant series for the Bovespa index were deaths (cases) in France, Brazil, and Italy (UK, Hubei, and Italy). It also indicates waves 1 and 4 are the periods when the Bovespa index has been mostly affected by COVID-19 data, implying that the local health conditions may modulate the importance of international health data to home country stock markets. Furthermore, these results show both local and international deaths series have impacted the Bovespa index more forcefully than their cases counterpart, and that there is prevalence of impacts in long run frequencies as compared to short term frequencies. Finally, the Bovespa Index response to COVID-19 news has evolved as the pandemic consolidated, transitioning from a response more self-centered to a more sensitive to international data.

Considering the partial phase differences, we find that on the onset of the pandemic, the COVID-19 series - particularly cases in Brazil, deaths in Brazil, France, Italy, and UK -, have led and negatively impacted the long run components of the Brazilian stock market.

On the contagion side, the decrease in dissimilarity in particular moments strongly suggests presence of contagion among the Brazilian sectors and that it is more relevant in lower frequencies and during the first wave. The VaR ratio analysis reinforce the evidence of contagion between the Brazilian sectors during the COVID-19 pandemic.

Overall, the results suggest that the Brazilian stock market responded vigorously to COVID-19 local and international data and that

---

5 On the financial COVID-19 literature the main approach has been to identify structural breaks in the financial data involved. For instance, Belhassine and Karamti (2021) employed the Perron (1997) breakpoint test in returns series. Our approach is derived from epidemiology and identify patterns in the deaths data directly.

6 Refer to http://nefin.com.br/risk_factors.html.

7 Despite being a highly informative database, there are few sector studies focusing Brazil. Some of the most relevant are Righi et al. (2012), Almeida et al. (2012), Righi et al. (2014) and Matos et al. (2017).
this response varies over frequencies, being modulated by the local stage of outbreak. The results also suggest a higher response to deaths data and that both market wide response and sector contagion are concentrated on longer term frequencies. Thus, our findings seem to be useful both to investors - in augmenting risk management practices - and policy makers that are compelled to cooperate.

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

2. Methodology

2.1. The continuous wavelet transform

The wavelet transforms originally explored empirically by Grossmann and Morlet (1984) are widely applied in some areas, as physics and medicine. It has also been used in economics, since pioneer works of Ramsey and Zhang (1996 and 1997) and Ramsey and Lampart (1998), and in finance, as in Rua and Nunes (2009), and Reboredo and Rivera-Castro (2014). Due a more flexible approach, based on a local base function that adjust the window width to deal with different frequencies, the wavelet transforms to overcomes the main drawbacks of the Fourier transform. Given a time series \( x(t) \), its continuous wavelet transform (CWT) is defined as:

\[
W_c(\tau, s) = \int_{-\infty}^{+\infty} x(t) \frac{1}{\sqrt{s}} \psi^* \left( \frac{t - \tau}{s} \right) dt
\]

where \( s \) is the scaling factor, \( \tau \) the translation parameter, \( \psi \) is the mother wavelet function, and \( \psi^* \) denotes the complex conjugation. The factor \( 1/\sqrt{s} \) is added to guarantee preservation of the unit energy (\( \psi_{t,s} = 1 \)), low scales are captured rapidly changing detail generating a compressed wavelet (\( |s| < 1 \)), capturing high frequencies movements, and high scales capture slowly changing features (\( |s| > 1 \)), or low frequencies movements (Rua, 2012). The basis function \( \psi_{t,s} \) must obey some conditions, such as admissibility\(^8\), similarity\(^9\), regularity, vanishing moments and invertibility. Once that the energy of the original signal \( x(t) \) is preserved by the wavelet transform if the admissibility condition is satisfied\(^11\) there should be at least one reconstruction formula for recovering the signal exactly from its wavelet coefficients and for allowing the computation of energy or other invariants directly from them.

There are many options of mother wavelet functions.\(^{12}\) Aguiar-Conraria and Soares (2011) suggests an analytic wavelet\(^{13}\) to study the synchronism between time series, once it provides an estimate of the instantaneous amplitude and instantaneous phase of the signal in the neighboring of each time/scale location \((\tau,s)\). On subset of analytic wavelet, the Morlet mother wavelet is the most popular alternative (Goupillaud et al., 1984), which is defined as:

\[
\psi_{\omega_0}(t) = \pi^{-1/4} e^{i\omega_0 t} e^{-t^2/2}
\]

where \( i = \sqrt{-1} \) is an imaginary number and the non-dimensional frequency \( \omega_0 \) is set \( \omega_0 = 6 \) to satisfy the admissibility condition (Torrence & Compo, 1998). As the wavelet transform decomposes the original signal in a time-scale domain, it’s necessary to convert scale into frequency. By the scale relationships (for additional details, see Aguiar-Conraria et al., 2008), the choice of \( \omega_0 = 6 \) give us a conversion ratio equal \( \omega = \omega_0 \approx 1 \). This direct correspondence between scale and frequency is ideal to simplify an effective interpretation of the results.

Finally, because the CWT is applied on finite-length time series, border distortions will occur due the fact that values of the transform at the beginning and the end of the sample are imprecisely computed, which involve artificial padding on the extremes of the sample (the most common is set zero to extend the time series).

\(^{8}\) The Fourier transform summarizes the data as a function of frequency and does not preserve information in time ( Gençay et al., 2001). It does not allow decompose signals into different scales, which limit his applicability to study signals that exhibit bursts of volatility, abrupt regime changes, or non-stationary (In & Kim, 2013).

\(^{9}\) For an integrable function, it means that its average should be zero and the function needs to be localized in both time and frequency space ( Gençay et al., 2001).

\(^{10}\) The scale decomposition should be obtained by the translation and dilation of only one mother wavelet function. This dilation procedure allows an optimal compromise in view of the uncertainty principle: The wavelet transform gives very good spatial resolution in the small scales and very good scale resolution in the large scales (Farge, 1992).

\(^{11}\) By the admissibility condition we have \( \int \frac{|x(t)|^2}{s} \, dt = \frac{1}{C} \int \int |W_c(\tau, s)|^2 \, dt \, ds \).

\(^{12}\) Such as Daubechies, Haar, Morlet, Meyer, for instance.

\(^{13}\) An analytic wavelet is a complex wavelet such that its Fourier transform is zero for negative frequencies \( \omega < 0 \).
(COI) is the region of the wavelet spectrum in which edge effects become important by a factor of $e^{-2}$. In Morlet wavelet cases this is given by $\sqrt{2s}$.

2.2. Wavelet tools

2.2.1. Wavelet power spectrum and Global Wavelet Power Spectrum

The wavelet power spectrum (WPS) reports the variance distribution of the original time series $x(t)$ throughout the time-frequency plane. It captures the energy of the CWT at each point in the time-scale domain, allowing the identification of most representative scales, that is, those contributing the most to the series total energy. Following Torrence and Compo (1998) we define the WPS by:

$$WPS_x(t, s) = |W_x(t, s)|^2$$  \hspace{1cm} (4)

To compare the oscillation in energy among a range of bands (or frequency) we define the Global Wavelet Power Spectrum (GPWS), which takes the average of wavelet power spectrum over all times (Aguiar-Conraria and Soares, 2011):

$$GWPS_x(t, s) = \frac{1}{2\pi} \int_{-\infty}^{+\infty} |W_x(t, s)|^2 dt$$  \hspace{1cm} (5)

2.2.2. Partial wavelet coherence and partial phase difference

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 during the pandemic period. 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, $z$. To do this, we follow Mihanović et al. (2009), and Aguiar-Conraria and Soares (2014) by using the partial wavelet coherence and partial phase-difference.

Before defining these high-order wavelet tools it’s necessary to present the wavelet coherence and phase-difference on bivariate cases. Let us first define the cross-wavelet transform (Torrence & Compo, 1998) as follows:

$$W_x(t, s) = W_x(t, s)W_y^*(t, s)$$  \hspace{1cm} (6)

where $W_x(.)$ and $W_y(.)$ are continuous wavelet transform of $x(t)$ and $y(t)$, respectively, and $^*$ denotes the conjugates complex. As the cross-wavelet transform is complex, we can express the cross-wavelet spectrum (XWT) as $|W_{xy}(t, s)|$. It computes the local covariance between two signals at each time-scale point.

The complex wavelet coherence between $x(t)$ and $y(t)$ is defined by:

$$\rho_{xy} = \frac{S(x^{-1}W_{xy}(t, s))}{S(x^{-1}|W_x(t, s)|^2)S(y^{-1}|W_y(t, s)|^2)}^{1/2}$$  \hspace{1cm} (7)

where $S(.)$ expresses a smoothing operator in both time and scale, $^s$ is a normalization factor ensuring the conversion to an energy density. Following Torrence and Webster (1999), the squared wavelet coherence is denoted as:

$$R_{xy}^2(t, s) = \frac{|S(x^{-1}W_{xy}(t, s))|^2}{S(x^{-1}|W_x(t, s)|^2)S(y^{-1}|W_y(t, s)|^2)}$$  \hspace{1cm} (8)

The wavelet coherence coefficient is in the range $0 \leq R_{xy}(t, s) \leq 1$. Once that the wavelet transforms conserves variance, the wavelet coherence is a good representation of the normalized coherence between two-time series (Torrence and Compo, 1998), where the closer to zero (one) the coherence, the weaker (stronger) the local correlation between the time-series.

Although the wavelet coherence computes the degree of local linear correlation between two signals, it does not reveal patterns of lead-lag relationship neither if the movements are positives or negatives. To deal with these limitations, the phase difference examines the delays in the oscillations between the two time-series. Following Torrence and Webster (1999) we define the phase difference as:

$$\phi_{xy}(t, s) = \tan^{-1}\left(\frac{\Re\{S(x^{-1}W_{xy}(t, s))\}}{\Im\{S(x^{-1}W_{xy}(t, s))\}}\right), \text{ with } \varphi \in [-\pi, \pi]$$  \hspace{1cm} (9)

where the smoothed real ($\Re$) and imaginary ($\Im$) parts should already be calculated in the wavelet coherence function. A phase-difference of zero indicates that the time-series move together at the specified frequency. If $\phi_{xy} \in \left(0, \frac{\pi}{2}\right)$ the series move in phase, but the time-series $x$ leads $y$, while if $\phi_{xy} \in \left(-\frac{\pi}{2}, 0\right)$ then it is $y$ that is leading. A phase-difference of $\phi_{xy} = \pm\pi$ indicates an anti-phase relation. Finally, if $\phi_{xy} \in \left(\frac{\pi}{2}, \pi\right)$, then $y$ is leading and time-series $x$ is leading if $\phi_{xy} \in \left(-\pi, -\frac{\pi}{2}\right)$.

Following Mihanović et al. (2009) and Aguiar-Conraria et al. (2018), for case of three series, the complex partial wavelet coherence between $x(t)$ and $y(t)$, after controlling for $z(t)$ is given by:
2.2.3. Wavelet spectra dissimilarity

Building on the work of Rouyer et al. (2008), Aguiar-Conraria and Soares (2011) developed a metric to measure the distance (dissimilarity)\footnote{There are many dissimilarity metrics developed with wavelets, but they are in majority based on discrete rather than on the continuous transforms used in this study. For instance, see Chan et al. (2003), Zhang et al. (2006) and Montero and Vilar (2014). Also, Aguiar-Conraria and Soares (2011) conveniently provide replicability codes for they implementation.} between the wavelet transforms of pairs of time series, such two \(F\overline{C}T\) wavelet transforms \((W_x\) and \(W_y\)). This metric can be used in cluster analysis. Also, comparing this measure before and during/after a crisis one can get information about how synchronization/linkage between financial markets components evolved, that is, the dissimilarity can be used as an indicator of contagion. In this study, we use this metric to study contagion among the Brazilian sector indices.

The authors use the singular value decomposition (SVD) of the cross-correlation spectrum \(W_x(\tau, s)W_y(\tau, s)\) to focus on the common high-power time-frequency regions. The method extracts components that maximize covariances of the pair of given wavelet spectra with the first component being the most important common patterns between as \(W_x(\tau, s)\) and \(W_y(\tau, s)\). Given the SVD, we compute the \(K\) most relevant vectors – the leading patterns \(\hat{f}_k\) and \(\hat{f}_k; k = 1, \ldots, K\) and singular vectors, \(u_k\) and \(u_k; k = 1, \ldots, K\), with \(K < F\) – which will approximately reconstruct the original matrices: \(W_x \approx \sum_{k=1}^{K} u_k \hat{f}_k\) and: \(W_y \approx \sum_{k=1}^{K} u_k \hat{f}_k\).

As the components of leading vectors and leading patterns are complex numbers, the distance between two wavelet spectra reduced to a few components is given by the angle between each pair of corresponding segments. Using the Hermitian approach\footnote{The Hermitian inner product of two complex vectors \(a\) and \(b\) is defined by \(a, b_C = a^* b\) and the norm is given by \(|a| = \sqrt{a, a_C}\), the Hermitian angle between the complex vectors \(a\) and \(b\) is determined by the formula: \(\cos(\Theta_H) = \frac{|a| b_C}{|a||b|}\), \(\Theta_H \in [0, \frac{\pi}{2}]\).} to define the angle of a complex vector space, the wavelet spectra distance between \(W_x\) and \(W_y\) is computed as

\[
d(W_x, W_y) = \frac{\sum_{k=1}^{K} \sigma_k^2 d(\hat{f}_k, \hat{f}_k) + d(u_k, u_k)}{\sum_{k=1}^{K} \sigma_k^2}
\]

where \(d(.)\) is the distance function\footnote{The distance between two-vectors \(p = (p_1, \ldots, p_m)\) and \(q = (q_1, \ldots, q_m)\) with \(M\) components in \(C\) is defined by: \(d(p, q) = \frac{1}{\sqrt{M}} \sum_{i=1}^{M} \theta_{H}(s_i^p, s_i^q)\). Where the \(i\)-th segment \(s_i^p\) two-vectors \(s_i^p := (i + 1, p_{i+1}) - (i, p_i) = (1, p_{i+1} - p_i)\).} and \(\sigma_k^2\) are the weighs equal to the squared covariance by each axis.

2.2.4. Wavelet-based value at risk (VaR)

To further investigate the contagion in the Brazilian economic sectors, we follow Rua and Nunes (2009) performing a wavelet-based Value at Risk (VaR) exercise. 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 \(1 - \alpha\) confidence level can be defined in the following manner:

\[
\text{VaR}(\alpha) = Io \Phi^{-1}(1 - \alpha) \sigma_p
\]

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

\[
\sigma_p^2 = \sum_{i=1}^{n} w_i^2 \sigma_i^2 + \sum_{i=1}^{n} \sum_{j=i+1}^{n} w_i w_j \text{Cov}(r_i, r_j)
\]

where \(w_i, \sigma_i,\) and \(r_i\) represents the weight of asset \(i\) in the portfolio, its volatility, and its returns, respectively.

As one can see, the portfolio variance can be decomposed in two factors, the first formed by the variances of its components and the second formed by the connection between its components, the covariances. To study how the linkages between the components of a portfolio has evolved, following Rua and Nunes (2009), we examine the ratio between the variance of the portfolio computed with the full expression of (13) and the variance computed excluding the covariance terms in (13).
The intuition is that if this (VaR) ratio increases, it means there is an increase in co-movement of the components normalized by their variances, translating in more connection among the portfolio components even when controlling by individual component variances.

However, we do not use time series expressions for computing (13), but instead we use time-frequency domain wavelet-based analog measures of variance and covariance. That is, we use the Wavelet Power Spectrum and Cross-Wavelet Transform described in (4) and (6) respectively. This procedure allows us to observe how the connections have changed in time and frequency through 3 dimensional maps, enabling the time and frequency evaluation of contagion.

2.3. Date stamping the COVID-19 waves

To provide comparative analysis on relevant sections of the pandemic, following Zhang et al. (2021), we have considered that the COVID-19 waves are characterized by a sequence of sustained upward and downward trend periods. Specifically, we have applied the Harding and Pagan (2006) method to identify the upward and downward trend periods contained on the COVID-19 world deaths data. The date stamping performed can be found on the online appendix (Figure A-1). The 4 COVID-19 waves identified are from January 22, 2020, to May 28, 2020, from May 29, 2020, to October 02, 2020, from October 03, 2020, to March 16, 2021, and from March 17, 2021, to July 2, 2021.

3. Data and empirical results

3.1. Data

Our complete sample is from April 30, 2018, to August 31, 2021, at a daily frequency. Following Akhtaruzzaman et al. (2021) and Costa et al. (2021), we have considered the COVID-19 period to begin on December 31, 2019 - the day cases of pneumonia detected in Wuhan, China, are first reported to the WHO. The pandemic period goes to the end of our sample, on August 31, 2021. Considering we intended to perform comparative static analysis using both the dissimilarity and Wavelet based VaR ratio, the pre-COVID-19 period was defined to begin on April 30, 2018, so that the pre-COVID-19 and the COVID-19 periods to have the same length.

The health dataset is comprised of series of deaths and cases of COVID-19 in the most affected countries by June 30, 2020: US, Brazil, United Kingdom, Italy, and France. We also use data from China and its Hubei Province to allow analysis of early stages pandemic impacts. World data is included for robustness. Following Karamti and Belhassine (2021), the COVID-19 data is transformed into daily growth rates. The data source is the Center for Systems Science and Engineering (CSSE) at the Johns Hopkins University (JHU). For more details on this dataset, refer to Dong et al. (2020). The COVID-19 data is available from January 22, 2020.

Concerning the financial variables, we use daily percent returns on the main broad Brazilian stock index, the Bovespa Index (BVSP), 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 formed by the most representative and traded stocks on Brasil Bolsa Balcão (B3), total return indices, are rebalanced four-monthly, and, except for IEE, are weighted by market cap. IEE is an equally weighted index.

According to the B3 definition, Basic Materials (IMAT) include 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. Electric Energy (IEE) is the only index considered containing only one economic segment. The data source for financial variables is Investing.com.

In our partial coherence exercise, we control for a specific set of instruments, the 5 Brazilian risk factors published by the Brazilian Center for Research in Financial Economics at the University of São Paulo. They are comprised of the three factors in the Fama and French (1993) model (Market Factor, Small minus Big, and High minus Low), the moment factor in line with Grundy and Martin

---

17 Policymakers and researchers describe the COVID-19 epidemics by waves without a common vocabulary on what constitutes an epidemic wave (Zhang et al., 2021). Considering this lack of uniformity on the literature, our attempt is intended to avoid more discretionary forms of setting intervals of interest for comparative analysis.

18 We considered a wave a sequence of an upward trend followed by one downward trend. 5 upward trends and 4 downward trends have been identified. See the online appendix (Figure A-1).

19 At this stage, the virus was still unknown. For a complete list of early COVID-19 key dates see Table 1 of Corbet, Larkin, and Lucey (2020).

20 When the COVID-19 data are employed, the actual analysis begins on the day the underlying COVID-19 series presents its first nonzero data. The cases in Brazil, France, Italy, and the UK are nonzero from Feb/26, Jan/24, Jan/31 and Jan/31. The deaths in Brazil, France, Italy, UK, and US are nonzero from Mar/17, Feb/15, Feb/21, Mar/06 and Feb/29. The remaining series are nonzero from Jan/22.

21 Refer to http://nefin.com.br/risk_factors.html.
and the illiquidity factor discussed in Amihud (2002). As we are using the returns on the Brazilian market as the explained variable at this exercise, we have used the first lag of the Market Factor. The remaining factors are aligned in time with the dependent variable.

Fig. 1 (Panel A) shows the cumulative returns on the Bovespa Index and its sectoral components during the pandemic period. It is noteworthy the considerable drawdowns seen in March of 2020, between 34.0% (Electrical Energy – IEE) and 54.4% (Real State – IMOB). We also highlight a strong convergence of patterns up to August 2020 (strong drawdowns followed by steady and partial recovery). This convergence seems to be somewhat present by the end of the sample, as a similar pattern for the Bovespa and most sector indices is observed, with small cumulative gains or losses. The exceptions are Basic Materials (IMAT), with a gain of 75.3%, and Real Estate (IMOB), with a loss of 42.7%.

The 7 days moving average of COVID-19 deaths in the selected localities Fig. 1 (Panel B) show that most time series present a two cycles pattern with a first peak in April 2020 and a second in February 2021. Brazil is an outstanding exception, with the local maximums in July 2020 and April 2021. The world data shows four well defined local maximums.

As for the moving average of cases, shown in Fig. 1 (Panel C), we highlight the world data, where a quasi-monotonic increase is perceived from February 2020 up to January 2021. Also, the US had a very similar behavior to the world, and Brazil did not reach a maximum up to the end of July 2020. From that point on, Brazil sustained a decrease which was followed by a relatively smooth increase that peaked in April 2021.

It is noteworthy, and relevant to the present study, the fact that we have an apparent different behavior in series of deaths and cases: deaths have declined in a more monotonic form 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 and vaccines, is more evident for world, European countries, and China, while in Brazil and US one 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.

Descriptive statistics are on Table 1. The pandemic period has been noticeably more volatile, with daily maximums and minimums returns of all considered stock indices occurring during the pandemic. Also, standard deviations have been increased. Skewness has decreased, turning negative for all indices during the COVID-19 period. Kurtosis has increased considerably, indicating higher incidence of extreme values during the pandemic.

Fig. 2 shows the Bovespa Index Wavelet Power Spectrum (WPS) and Global Power Spectrum (WGPS). We emphasize, first, that the spectrum varies along the time and frequency, indicating the non-stationarity of data and suitability of the method employed. Second, that the mean power decreases from the highest to the lowest frequencies, with most of the variability of the series being attributed to periods from 2 to 32 days. This behavior does not change qualitatively for the sector indices considered, see the online appendix (Figure A-2). Thus, we have considered 2–8 days to be short run and 8–32 days to be the long run on the analysis that follow.

3.2 COVID-19 effect on Brazilian stock market index (Bovespa Index)

Our first empirical exercise uses wavelet partial coherences and partial phase-differences aiming to show how COVID-19 deaths and cases in different localities are related to returns on the Bovespa Index after controlling for the Brazilian stock market main risk factors.

Fig. 3 reports the wavelet partial coherences and phase-differences between the Bovespa and the COVID-19 cases (Fig. 3.a to Fig. 3.h) or deaths (Fig. 3.i to Fig. 3.p) on all the selected locations. Partial wavelet coherencies are plotted as 2-dimensional heat-maps, with warmer colors representing higher coherences (unity coherence is depicted in red, and nearly null coherences in blue). The arrows are drawn on regions of higher partial coherences and indicate the partial phase-differences. That is, an arrow pointing right (left, up, down) corresponds to a partial difference of zero (±π, π/2, -π/2). The cone of influence, region of the wavelet spectrum in which edge effects become important, is delimited with a black convex line and shaded.

Regarding statistical significance, as usual on the related literature, we use Monte Carlo Simulations to construct significance contours for the partial coherences. Black (grey) contours refer to 5% (10%) significant regions.

As one can see on Fig. 3, there are many regions on the time-frequency plane in which high and significant partial coherence is found. To analyze these findings, we first focus on more general conclusions, that can be drawn considering mainly the relative size of the regions showing significant coherence. For instance, in this first stage we identify the most relevant COVID-19 wave to be the first (from January 22, 2020, to May 28, 2020) considering that in this first wave we have a higher share of the time-frequency plane covered by high and significant coherence. After that we highlight some keynote areas with high and significant coherence using the phase differences.

As anticipated, looking at all considered frequencies (2–32 days periods) and all series (cases and deaths), the first wave presents the highest amount of significant coherence area, with a mean share of 6.5% across all series. The fourth wave presents the second

---

22 We have tested the best number of lags to include, from zero up to 5. The first lag alone has provided the best fitted model considering both the Akaike and Bayesian Information Criterion.

23 Actually, from January 29, 2020, to August 31, 2021, representing the period with COVID-19 moving average data.

24 Because one is dealing with finite-length time series, errors will occur at the beginning and end of the wavelet power spectrum (Torrence & Compo, 1998).

25 As discussed on the methodology section, we have identified 4 COVID-19 waves periods: from January 22, 2020, to May 28, 2020, from May 29, 2020, to October 02, 2020, from October 03, 2020, to March 16, 2021, and from March 17, 2021, to July 2, 2021.
Fig. 1. Cumulative returns on the Brazilian stock market, Bovespa, and its sector indices, and COVID-19 numbers on selected locations. Notes: The World COVID-19 data uses the right-side scale, all the other series the left-side scale. Data from January 22, 2020, to August 31, 2021. Authors elaboration with data from investing.com and Johns Hopkins Corona Virus Research Center.
The wave 4 is slightly more affected by the COVID-19 data than wave 1, with shares of 4.7% and 4.4% respectively. In this case the wave 2 is once more the less affected, with a share of 1.3%. However, looking only to the short run periods (2–8 days), the wave 4 is slightly more affected by the COVID-19 data than wave 1, with shares of 4.7% and 4.4% respectively. In this case the wave 2 is once more the less affected, with a share of 1.3%.

Desegregating the analysis of cases and deaths, one sees a similar pattern, with the wave 1 being the most critical moment for both cases and deaths separately, followed by wave 4. The wave 2 being again a relatively unimportant period in terms of impacts of COVID-19 to the Brazilian stock market.

A first conclusion that we drawn is that the wave 1 and 4 seems to be the periods when the Bovespa index has been mostly affected by COVID-19 data. This conclusion seems to hold whether we consider cases and deaths separately or desegregate by long and short run frequencies, here defined as the components of period of 8–32 days.

The same order of incidence is perceived when analyzing the long run (8–32 days periods), with a wave 1, wave 2 and wave 4 presenting 8.8%, 2.5% and 0.7% shares respectively.

However, looking only to the short run periods (2–8 days), the wave 4 is slightly more affected by the COVID-19 data than wave 1, with shares of 4.7% and 4.4% respectively. In this case the wave 2 is once more the less affected, with a share of 1.3%.

Desegregating the above analysis to cases and deaths, one sees a similar pattern, with the wave 1 being the most critical moment for both cases and deaths separately, followed by wave 4. The wave 2 being again a relatively unimportant period in terms of impacts of COVID-19 to the Brazilian stock market.

A first conclusion that we draw is that the wave 1 and 4 seems to be the periods when the Bovespa index has been mostly affected by COVID-19 data. This conclusion seems to hold whether we consider cases and deaths separately or desegregate by long and short run frequencies. These waves, 1 and 4, also coincides with periods of high incidence of COVID-19 on Brazilian soil (see Fig. 1 and discussion on Section 3.1), indicating that the local health conditions may modulate the importance of international health data to home country stock markets.

Considering now all the COVID-19 series analyzed along the entire COVID-19 period, the significant areas are more present on the long run frequencies (4.2%) than on the short run frequencies (3.2%). The long run also shows more significant area when desegregating the series in cases and deaths. To be specific, for the cases (deaths), the mean value is 2.8% (3.5%) on the short run versus a mean of 3.5% (4.8%) on the long run. Put differently, there is evidence that the COVID-19 effect over the Bovespa index has been more pronounced on longer terms frequencies, here defined as the components of period of 8–32 days.

Comparing the mean effect of cases and deaths during the entire pandemic period, both on the short and long run (2–32 days periods) the deaths series show a higher mean incidence of significant area when compared to the cases series, 4.2% vs 3.2%.

Considering now each locality series, during the most critical moments to Brazil, waves 1 and 4, there is a higher relevance of deaths series measured by the share of significant area. For instance, during the wave 1, cases in Brazil (world) exhibit a 11.6% (5.7%)
significant area, while the deaths in Brazil (world) a 14.6% (7.1%) share. During the wave 4 these shares are 1.9% (2.4%) and 4.1% (2.8%) respectively. Thus, we have found evidence that both local and international deaths series have impacted the Bovespa index more forcefully than their cases counterpart, especially during the most critical moments in terms of the local pandemic.

Looking now at the hole period analyzed, considering all frequencies, considering the incidence of significant coherence areas, the most (least) relevant series are deaths (cases) in France, Brazil, and Italy (UK, Hubei, and Italy) in this order. If one considers only the first wave, the most (least) relevant series are deaths in Brazil, cases in Brazil, and deaths in UK (cases in UK, Italy, and China). These finding support that the response to COVID-19 news has evolved as the pandemic consolidated, transitioning from a response more self-centered at first to one more sensitive to international data as the pandemic status materialized. This variable response along the time once more justifies the use of wavelet-based methods here employed.

Regarding the world deaths, it is found to be of relevance, the fifth (sixth) with the highest significant coherence areas shares during the hole period (the first wave). This seems to validate the use of worldwide COVID-19 data seen in the literature, as in Karamti and Belhassine (2021), for the Brazilian case.

Having delineated above the main general results, we next describe in more details a few selected high and significant partial coherence spots we believe are the most relevant, looking more closely to the phase differences presented so we can infer lead-lag and signal information.

First, we highlight the series with the highest impacts (larger partial coherence areas) during the first COVID-19 wave and considering only the long run (8–32 days periods). Namely, we are looking at the bottom left region of plots of cases in Brazil (Fig. 3.a), deaths in Brazil (Fig. 3.i), France (Fig. 3.k), Italy (Fig. 3.m), and UK (Fig. 3.n). On all the significant partial coherence spots presented in this time-frequency region of above listed series, the arrows are mostly pointing towards the second quadrant, indicating a partial phase difference between $\pi/2$ and $\pi$. These findings suggest that, on the onset of the pandemic and after controlling for local market

---

Fig. 2. Bovespa daily percent returns (left), its Wavelet Power Spectrum (center) and its Global Wavelet Power Spectrum (right).

Notes: The black contours on the Wavelet Power Spectrum (WPS) plot refers to 5% significance and is theoretically obtained considering a AR(1) process as the null hypotheses. In the heatmap, colder colors represent lower power while warmer colors represent higher power. The shaded area outside the Cone of Influence is subject to edge effects. The sample is from April 30, 2018, to December 30, 2019, for the COVID-19 period (top) and from December 31, 2019, to August 31, 2021, for the COVID-19 period (bottom). Authors elaboration with data from investing.com. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

---

26 Among the cases series, the most relevant have been Cases in France, Brazil, and the US in this order.
risk factors, the COVID-19 series have led and negatively impacted the long run components of the Brazilian stock market. We understand this to be a very intuitive result, showing the market participants mostly reacted negatively (positively) to the increase (decrease) in the COVID-19 numbers incorporating a lower (higher) long run expectations to the asset prices on the first stages of the pandemic.

Finally, we look at the COVID-19 series with the highest impacts on the short term (2–8 days periods) during the fourth wave (from March 17, 2021, to July 2, 2021), in its turn the period when the short-term were more forcefully impacted. The selected series are cases in China (Fig. 3.b), and deaths in China (Fig. 3.j), France (Fig. 3.k), Hubei (Fig. 3.l), and Italy (Fig. 3.m). On this sample, we see mixed results. For cases and deaths in China and Hubei, a nearly zero partial phase is observed, indicating these COVID-19 series are in phase with the Bovespa index, meaning a positive response but no clear leading. For the deaths in France and Italy, the arrows are pointing left, indicating a partial phase difference of around π, meaning that these European COVID-19 series were negatively related to the short run components of returns on the Brazilian stock during the last studied pandemic wave.

3.3. Brazilian sectorial contagion

Given the dramatic turmoil experienced in the stock markets during COVID-19 pandemic, sometimes of unprecedented magnitude, as shown in Baker et al. (2020), and the asymmetric effects on markets shown, for example, in Mazur et al. (2021), we also study possible contagion effect among sectors in the Brazilian economy. Specifically, we propose evaluating the sectoral contagion among the Bovespa index sector components during the pandemic spread using both the wavelet dissimilarity and wavelet based VaR ratio. We evaluate the evidence of sectorial contagion, defined, in line with Forbes and Rigobon (2002). That is, we define contagion as the increase of linkage among the Bovespa sector components from the baseline period of pre-COVID-19 to the COVID-19 period and its waves.

Table 2 reports the dissimilarity metric for each pair of Brazilian sector index during a set of periods, namely, the pre-COVID-19 period, the entire COVID-19 period, and the four COVID-19 waves identified.

For this first analysis, we take the average of the dissimilarity measure as being inversely related to the average linkage between sectors. Thus, a decrease (increase) in the average dissimilarity would mean an increase (decrease) in average linkage between sectors, indicating presence (absence) of sectorial contagion in average. Table 2 presents results for all the frequencies considered, from 2 to 32 days periods. For saving space, we are not reporting the complete tables for short run (2–8 days periods) and long run (8–32 days periods) dissimilarities.

Table 3 presents the averages of dissimilarity between the sector indices, including the short and long run in separate. This finding indicates that the contagion is more evident for the long run frequencies. For instance, the decreased dissimilarity is found in every wave regarding the long run components (8–32 days periods) as well as for the entire COVID-19 period. Also, the mean dissimilarity during the first wave represents only 68.9% of the dissimilarity during the baseline period of pre-COVID-19, implying a considerable increase in linkage between sectors. In another hand, contagion is found only during the first two waves when one considers the short run components.

Overall, we understand that the results on dissimilarities strongly suggest the presence of contagion among the Brazilian sectors during COVID-19 pandemic, and that contagion is particularly relevant in lower frequencies and during the first wave.

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 Fig. 4.

As discussed on the methodology section in more details, this analysis is based on the ratio between the VaR computed considering co-movement (covariance) and the VaR considering no co-movement (covariances set to zero). As this ratio increases, the co-movement normalized by the variances increases, indicating an increase in linkages that cannot be attributed to heteroscedasticity. In this context, using the wavelet analogous of variance and co-variance on the computation is important to enable heterogeneity in time and frequency.

Fig. 4 shows the VaR ratio performed considering the portfolio comprised of all 7 Brazilian sector indices under consideration at this paper. Higher (lower) values of the VaR ratio are depicted in warmer (cooler) colors, according to the intensity scale on the right side of the figure. Values above unity indicate the co-movements among portfolio components increase the portfolio volatility in a given time-frequency point.

Also, the transition from a cooler to a warmer color indicate the increase of linkage among portfolio components, that is, contagion. In this exercise we are particularly interested in mean values of the VaR ratio during specific times (the pre-COVID-19 period as a baseline, the complete COVID-19 period, and the 4 waves identified in this study) and across specific frequencies (short run, long run). We are also interested in dark red spots, which indicate the time-frequency regions where the (normalized) co-movement has been

---

27 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.
28 For exactly dates see notes of Table 2 and discussion on the methodology and data sections.
29 The dissimilarity tables for short and long run can be provided by the authors upon request.
30 The importance of accounting for heteroscedasticity on the identification of contagion is discussed in Forbes and Rigobon (2002).
31 We have also performed the VaR ratio analysis with all pair of sector indices taken individually. The conclusions do not change qualitatively and are reported in the online appendix (Figure A-3).
It is noteworthy the region of highest ratio clustered from the first days of February to the end of March, 2020, the most difficult period for the stock market, and practically crossing all the frequencies. Numerically, the mean VaR ratio is increased from 1.93 (1.81) to 2.21 (2.06) on the short (long) run components during the first wave of Covid, an increase of 14.0% (13.7%). Also, in average the increase of VaR ratio is present during the second (third) wave of COVID-19 considering only the short (long) run components. Overall, these results reinforce the evidence of presence of contagion between the Brazilian sectors during the COVID-19 pandemic.

Fig. 3. Partial Wavelet Coherence between the Bovespa Index and the COVID-19 data in selected locations while controlling for 5 risk factors. Notes: Colder colors represent lower partial coherence while warmer colors represent higher coherence. The black (grey) contours refer to levels of significance of 5% (10%) and are derived from Monte Carlo Simulation with 1000 runs. The arrows refer to partial phase-differences and are shown where the partial coherence is 0.8 or higher. The shaded area outside the Cone of Influence is subject to edge effects. The full sample is from January 22, 2020, to August 31, 2021. For each analysis the starting date is the first day a case (death) is recorded in the underlying locality. Authors elaboration with data from Investing.com (Financial Indices), Johns Hopkins University (COVID-19) and the Brazilian Center for Research in Financial Economics (NEFIN) at the University of São Paulo (Risk Factors). (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

maximum.
4. Conclusion

Brazil is one of the most affected countries in the world by the COVID-19 pandemic, either in number of cases or deaths. To be specific, as of August 31, 2021, Brazil was the third country with the most cases (20.8 million), behind the United States (39.2 million) and India (32.8 million). Looking at the cumulative number of deaths, Brazil had 580.4 thousand, second to only the United States, which accumulated 640.2 thousand.

During the period associated with the first wave of the pandemic in several countries in 2020, it is noteworthy the considerable drawdowns seen in March of 2020 on Brazilian stock indices, the sector indices declined between 34.0% (Electrical Energy – IEE) and 54.4% (Real State – IMOB). We also highlight a strong convergence of patterns up to august 2020 (strong drawdowns followed by stead and partial recover). This convergence seems to be somewhat present by the end of the sample, as a similar pattern for the Bovespa index and most sector indices is observed, with small cumulative gains or losses. The exceptions are Basic Materials (IMAT), with a gain
have shown higher incidence of significant partial co-movement with the Brazilian stock market as compared to the COVID-19 cases present in long term frequencies (8
August 31, 2021). Waves 1 to 4 are from Jan 22, 2020, to May 28, 2020, from May 29, 2020, to Oct 02, 2020, from Oct 03, 2020, to Mar 16, 2021, and among the Brazilian sectors from April 30, 2018, to August 31, 2021, at a daily frequency. In the world and the return on Brazilian broad stock market index, Bovespa index, as well as by investigating financial contagion relations in the time-frequency domain between the cases or deaths by COVID-19 in Hubei, China, in countries with record deaths and financial market reactions to the pandemic. We believe having filled the gap of the COVID-19 literature by studying the conditional late the importance of international health data to home country stock markets; The significant spots on partial coherence are more of 75.3%, and Real Estate (IMOB), with a loss of 42.7%. Regarding both contexts, our goal is to reconcile and thus measure and distinguish between short-term and longer-term Brazilian financial market reactions to the pandemic. We believe having filled 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, Bovespa index, as well as by investigating financial contagion among the Brazilian sectors from April 30, 2018, to August 31, 2021, at a daily frequency. Regarding the Brazilian market wide response, among several results, we emphasize that the most significant conditional relations – both local and international - and the Bovespa index is found during the first and fourth COVID-19 waves, coinciding with periods of higher incidence of COVID-19 on Brazil, indicating that the local health conditions may modu
series. Thus, we have found evidence that both local and international deaths series have impacted the Bovespa index more forcefully than their cases counterpart, especially during the most critical moments in terms of the local pandemic; Overall, the most (least) relevant series for the Bovespa index are deaths (cases) in France, Brazil, and Italy (UK, Hubei, and Italy) in this order. If one considers only the first wave, the most (least) relevant series are deaths in Brazil, cases in Brazil, and deaths in UK (cases in UK, Italy, and China). These finding support that the response to COVID-19 news has evolved as the pandemic consolidated, transitioning from a response more self-centered at first to one more sensitive to international data as the pandemic status materialized; On the onset of the pandemic and after controlling for local market risk factors, the COVID-19 series have led and negatively impacted the long run components of the Brazilian stock market.

Regarding the contagion, the results on dissimilarities strongly suggest its presence among the Brazilian sectors during COVID-19 pandemic, and that contagion is particularly relevant in lower frequencies and during the first wave. Considering the wavelet-based Value at Risk (VaR) exercise, it is noteworthy the region of highest ratio clustered from the first days of February to the end of March, 2020, the most difficult period for the stock market, and practically crossing all the frequencies. Numerically, the mean VaR ratio is increased from 1.93 (1.81) to 2.21 (2.06) on the short (long) run components during the first wave of covid, an increase of 14.0% (13.7%). Also, in average the increase of VaR ratio is present during the second (third) wave of COVID-19 considering only the short (long) run components. Overall, these results reinforce the evidence of contagion between the Brazilian sectors during COVID-19 pandemic.

We understand our findings are valuable for investor and portfolio managers alike. For instance, to observe the heterogeneity of impacts in the short versus long run and to better grasping the usefulness of deaths and cases series in a pandemic context can lead to better risk management practices. To the policymakers, our findings highlight the necessity of international cooperation, considering the spillovers effects detected.

Regarding both limitations and new research directions, we believe the generality of our findings is not totally stablished, once proper comparison with reactions to other pandemic episodes or at least with the COVID-19 pandemic reaction of highly similar financial markets (in some to-be-defined sense) is not in the scope of this paper.

Declaration of competing interests

None.

Authors statement

Antonio Costa: Conceptualization, Validation, Formal analysis, Investigation, Writing – original draft, Writing – review & editing, Methodology, Software, Visualization. Cristiano da Silva: Supervision, Conceptualization, Methodology, Software, Writing – original draft, Writing – review & editing Paulo Matos: Supervision, Conceptualization, Methodology, Writing – review & editing.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.iref.2022.05.010.
References

Aguiar-Conraria, L., Azevedo, N., & Soares, M. (2008). Using wavelets to decompose the time–frequency effects of monetary policy. Physica A, 387, 2863–2878.

Aguiar-Conraria, L., Martins, M., & Soares, M. (2018). Estimating the Taylor rule in the time-frequency domain. Journal of Macroeconomics, 57, 122–137.

Aguiar-Conraria, L., & Soares, M. (2011). Business cycle synchronization and the euro: A wavelet analysis. Journal of Macroeconomics, 33, 477–489.

Aguiar-Conraria, L., & Soares, M. (2014). The continuous wavelet transform: Moving beyond uni and bivariate analysis. Journal of Economic Surveys, 28, 344–375.

Akhtaruzzaman, Md, Boubaker, A., & Sensoy, A. (2021). Financial contagion during COVID-19 crisis. Finance Research Letters, 38, Article 101249.

Almeida, A., Frascaroli, B., & Cunha, D. (2012). Medidas de Risco e Matriz de Contágio: Uma Aplicação do CoVaR para o Mercado Financeiro Brasileiro. Revista Brasileira de Finanças, 10, 551–584.

Amihud, Y. (2002). Illiquidity and stock returns: Cross-section and time-series effects. Journal of Financial Markets, 5(1), 31–56.

Ashraf, B. N. (2020). Stock markets’ reaction to COVID-19: Cases or fatalities? Research in International Business and Finance, 54, Article 101249.

Baker, S., Bloom, N., Davis, S., Kost, K., Sammon, M., & Viratyosin, T. (2020). The unprecedented stock market impact of COVID-19, working paper N 26945. National Bureau of Economic Research.

Belhassine, O., & Karamti, C. (2021). Contagion and portfolio management in times of COVID-19. Economic Analysis and Policy, 72, 73–86.

Chan, F. K., Fu, A. W., & Yu, C. (2003). Haar wavelets for efficient similarity search of time series: With and without time warping. IEEE Transactions on Knowledge and Data Engineering, 15(5), 886–705.

Corbet, S., Larkin, C., & Lucey, B. (2020). The contagion effects of the COVID-19 pandemic: Evidence from gold and cryptocurrencies. Finance Research Letters, 35, Article 101554.

Costa, A., Matos, F., & da Silva, C. (2021). Sectoral connectedness: New evidence from US stock market during COVID-19 pandemics. Finance Research Letters, Article 101214.

Dong, E., Du, H., & Gardner, L. (2020). An interactive web-based dashboard to track COVID-19 in real time. The Lancet Infectious Diseases, 20, 533–534.

Donth, N., & Gustafsson, A. (2020). Effects of COVID-19 on business and research. Journal of Business Research, 117, 284–289.

Fama, E., & French, K. (1993). Common risk factors in the returns on stocks and bonds. Journal of Financial Economics, 33, 3–56.

Farge, M. (1992). Wavelet transforms and their applications to turbulence. Annual Review of Fluid Mechanics, 24(1), 395–458.

Ferré, K., & Gigobon, R. (2002). No contagion, only interdependence: Measuring stock market co-movements. The Journal of Finance, 57, 2223–2261.

Gencay, R., Selçuk, F., & Whitcher, B. J. (2001). Decomposition of Hardy functions into square integrable wavelets of constant shape. SIAM Journal on Mathematical Analysis, 15(3), 723–736.

Grundy, B., & Martin, S. (2015). Understanding the nature of the risks and the sources of the potential return. Investment Review of Financial Studies, 14(1), 29–78.

Harding, D., & Pagan, A. (2006). Synchronization of cycles. Journal of Econometrics, 132(1), 59–79.

Haug, A., & Morlet, J. (1984). Cycle-occtave and related transforms in seismic signal analysis. Geoeorxploration, 23(1), 85–102.

Haug, A., Morlet, J. (1984). Decomposition of Hardy functions into square integrable wavelets of constant shape. SIAM Journal on Mathematical Analysis, 15(5), 886–705.

In, F., & Kim, S. (2013). An introduction to wavelet theory in finance: A wavelet multiscale approach. World scientific.

Karamti, C., & Belhassine, O. (2021). COVID-19 pandemic waves and global financial markets: Evidence from wavelet coherence analysis. Finance Research Letters, 35, Article 101554.

Karamti, C., & Belhassine, O. (2021). Financial contagion during COVID-19 crisis. Global Business Review, https://doi.org/10.1177/09721509211026813.

Matos, P., Sampaino, G., & Castro, L. (2017). How important is forward-looking behavior in Brazilian sectoral indices risk premium? International Journal of Applied Economics, 14, 19–36.

Mazur, M., Dang, M., & Vega, M. (2021). COVID-19 and the march 2020 stock market crash. Evidence from S&P1500. Finance Research Letters, 38, Article 101690.

Mihanovi´c, H., Orlic, M., & Pasaric, Z. (2009). Diurnal thermocline oscillations driven by tidal flow around an island in the Middle Adriatic. Journal of Marine Systems, 78, S157–S168.

Monteiro, P., & Villar, J. A. (2014). TSClust: an R package for time series clustering. Journal of Statistical Software, 62(2014), 1–43.

Perron, P. (1997). Further evidence on breaking trend functions in macroeconomic variables. Journal of Economics, 80(2), 355–385.

Ramsey, J., & Lampart, C. (1998). The decomposition of economic relationship by time scale using wavelets: Expenditure and income. Studies in Nonlinear Dynamics and Econometrics, 3, 23–42.

Ramsey, J., & Zhang, Z. (1996). The application of wave form dictionaries to stock market index data. In Y. Kratsov, & J. Kadtke (Eds.), Predictability of complex dynamical systems. Springer.

Ramsey, J., & Zhang, Z. (1997). The analysis of foreign exchange data using waveform dictionaries. Journal of Empirical Finance, 4, 341–372.

Reboredo, J., & Rivera-Castro, M. (2014). Wavelet-based evidence of impact of oil prices on stock returns. International Review of Economics & Finance, 29, 145–176.

Righi, M., Ceretta, P., & Silveira, V. (2012). An introduction to wavelet theory in finance: A wavelet multiscale approach. World scientific.

Sharif, A., Aloui, C., & Yarovaya, L. (2020). COVID-19 pandemic, oil prices, stock market, geopolitical risk and policy uncertainty nexus in the US economy: Fresh evidence from the wavelet based approach. International Review of Financial Analysis, 70, Article 101496.

Zhang, D., Hu, M., & Ji, Q. (2020). Financial Markets under the global pandemic of COVID-19. Finance Research Letters, 36, Article 101528.

Zhang, S., Marioli, F., & Gao, R. (2021). A second wave? What do people mean by covid waves? A working definition of epidemic waves. MedRxiv. https://doi.org/10.1101/2021.02.21.21252147.