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PAULO ICARO BARROS RODRIGUES DA COSTA

BRAZILIAN BANKING CYCLE SYNCHRONIZATION DURING COVID-19 CRISIS

FORTALEZA
2021

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Dissertação apresentada ao Curso de Mestrado Acadêmico em Economia do Programa de Pós-Graduação em Economia do Centro de Pós-Graduação em Economia da Universidade Federal do Ceará, como requisito parcial à obtenção do título de mestre em Economia. Área de Concentração: Economia

Orientador: Prof. Dr. Paulo Rogério Faustino Matos

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À Deus.

Aos meus pais, Rizomar e Ana.

Aos meus irmãos, Cairo e Nicole.

À todos meus amigos.

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RESUMO

São avaliadas as relações condicionais no domínio tempo-frequência entre o retorno do índice financeiro brasileiro, IFNC, e casos ou mortes por COVID-19 em Hubei, em países que se destacaram nesse cenário de crise sanitária e no mundo, considerando o período de 29 de janeiro a 31 de agosto de 2020. Em seguida, é estudado o comportamento do setor bancário durante a pandemia através da análise dos co-movimentos entre bancos e por meio do desenho do *pass-through* do setor bancário. Metodologicamente, são adotados os trabalhos de Aguiar-Conraria *et al.* (2018) e Aguiar-Conraria e Soares (2011) no uso do instrumental de *wavelet*. São encontradas relações opostas e intuitivas entre a série financeira e os números de COVID-19. Os resultados sugerem que COVID-19 é crucial para descrever a intensidade dos co-movimentos entre bancos em 2020 e que ITSA3 e BPAN4 tem papéis-chave no *pass-through* do setor bancário. Tais resultados são importantes para explicar a reação do IFNC ao COVID-19, como este afetou as relações entre bancos e são úteis para descrever o *pass-through* do setor bancário.

Palavras-chave: COVID-19. Índice Financeiro Brasileiro. Instrumental de *Wavelet*. Causalidade de Granger. *Pass-Through* do Setor Bancário.

ABSTRACT

We assess the conditional relationships in the time-frequency domain between the return on Brazilian financial index, IFNC, and the COVID-19 cases or deaths in Hubei, in countries who stood out in this health crisis scenario and the world, considering the period from January 29 to August 31, 2020. Second, we study the banking sector behavior during the pandemic by analysing the co-movements between banks and by drawing a pass-through path inside the sector. Methodologically, we mainly follow Aguiar-Conraria *et al*. (2018) and Aguiar-Conraria and Soares (2011) by using the wavelet framework. We find some opposite and intuitive relationships between the financial series and COVID-19 data. We find COVID-19 is decisive in describing the intensity of co-movements between banks in 2020 and that ITSA3 and BPAN4 play key roles in the banking sector pass-through. Our findings are use useful to explain the reaction of IFNC cycles to COVID-19 cycles, how it impacts banks linkages and are helpful to describe the pass-through in the banking sector.

Keywords: COVID-19. Brazilian Financial Index. Wavelet Framework. Granger Causality. Banking Sector Pass-Through.

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1 INTRODUCTION

In 2020 the world has experienced an unprecedented crisis caused by an unknown respiratory disease that started in the end of 2019 in the Chinese city of Wuhan and quickly spread, taking world proportions by March 2020 when the World Health Organization declared COVID-19 a pandemic. By the end of August 2020[1], nearly 25.5 million cases and 850 thousands deaths had been confirmed, according to the World Health Organization. The impacts on the public health system worldwide were horrifying due to expectations that its capacity, in terms of hospital beds, necessary equipment and health professionals, could not bear the raising amount of the serious cases. Although mankind has experienced some pandemic scenarios before (e.g., Black Death in the middle ages, Spanish flu in the early 19's and Swine influenza more recently), none of these had achieved comparable proportions in terms of severe collateral economic and financial effects.

The governments, trying to avoid the worst scenario possible, imposed lockdowns rules and business activity restrictions in some sectors causing considerable economic damage as revenue descents, travel restrictions, job productivity losses, hospitality sector decline, business shutdowns (GOODELL, 2020). In US, findings report COVID-19 affected economic sectors in an asymmetric form (MAZUR *et al*., 2021), with some sectors experiencing benefits from theses impositions e.g., software and digital content industry, and was a decisive source for the increase of geopolitical risk level and economic uncertainty (SHARIF *et al*., 2020). With a sample over 6,000 firms of 56 economies, Ding *et al*. (2020) state that firms with some characteristics as robust pre-2020 finances and less exposure to COVID-19 through costumer localities and supply chain, were less susceptible to acute slumps in its stock prices.

In reaction to these real economic impacts, stock markets worldwide were expected to retract, once expectations about the COVID-19 numbers and the economy were not encouraging. Using data of 64 countries, Ashraf (2020) finds stock markets returns declined as the number of cases increased, and the reaction intensity varies according to the stage of outbreak. Making use of text-based methods, Baker *et al*. (2020) conclude COVID-19 outbreak influenced US stock market in a manner never seen before either in terms of volatility or market returns. They also highlight there were 18 market jumps in 22 trading days dating from February 24 to March 24, 2020, a fact unnoticed before in history.

[1] Over 102 million cases and nearly 2.21 million of deaths confirmed until January 2021 in the world according to World Health Organization.

Using the wavelet framework, Matos, Costa and da Silva (2021) find short-run cycles of deaths in Italy, in early March, and in the world, afterwards, leads (out-of-phase) US stock Market (S&P 500), which suffered cumulative loss over 30% during the period from February to April 2020. They also find that the Energy sector is the first to react to the pandemic and the Telecom sector is important to describe the pass-through between the sectors. Costa *et al*. (2021) state there seems to be a recurring presence of significant relations between Ibovespa and the COVID-19 measures, especially the death numbers, in the most hazardous moment of the pandemic, in late March 2020. Using Granger causality test, they also find presence of contagion between Brazilian sectors on all frequencies.

Given this pandemic context, many other studies emerged assessing the effects over the economic and financial environment (ALI *et al*., (2020); AKHTARUZZAMA *et al*., (2021); LYÓCSA *et al*., (2020); MACHMUDDAH *et al*., (2020); SIDDIQUI *et al*., (2020) and YAROVAYA *et al*., (2020)).

Although US soon emerged as the epicentre after China and Europe, it is worth noting the COVID-19 impact on developing countries, especially Brazil, which stood out in terms of both cases and deaths (more than 3.8 million cases and roughly 120.5 thousand deaths confirmed by the end of August 2020 according to World Health Organization) in the early stages of the pandemic and soon was only behind US. The first reason one can think is the large population Brazil has, however some other reasons can explain the fast spread inside its territory, the high number of deaths and also why Brazil is an interesting case to study: (i) the hospitals were not prepared, at first, to attend the growing numbers of critical cases, (ii) the presence of "favelas"[2] in urban areas, which are critical spread regions due to its high population density, (iii) the fact that political leaders minimized the COVID-19 surge despite rising numbers, giving the people a wrong picture about how serious the situation was, (iv) the promotion of medicines with no scientific base to treat COVID-19, mostly supported by political leaders, even when respected medical and scientific organization tightly discarded its usage, (v) moments of dissonance between the central and state level governments about how to cope with the situation, and (vi) countless times population itself disrespected the government procedures to slow down the disease advance.

Besides the points mentioned above, we emphasize the fact that the COVID-19 literature, albeit prolific, is mainly focused in developed countries impacts. Costa *et al*. (2021), for our

[2] Homes characterized for many poor families living in it and, usually, for the lack of basic infrastructure.

knowledge, is pioneer in studying these financial impacts for the Brazilian case. We follow them in providing one more study of COVID-19 effects over an important developing country.

In the international scenario, Da Silva *et al*. (2019) argue that financial integration benefits are economic efficiency and growth, nevertheless at the cost of being exposed to contagion. These two concepts (integration and contagion) are relevant to understand the reaction of worldwide financial markets to crisis scenarios (e.g., The Mexican peso crisis (1994), Asian financial crisis (1997), Dot.com bubble (late 1990s) and, recently, the US subprime crisis (2008)). In this perspective, assessing the effects over the financial sector, precisely the banking sector, also proves pertinent, once its idiosyncrasies, mainly due to the strong linkages between banks, turns it to be more susceptible to such events, even the non-financial ones, like COVID-19 pandemic.

Brazil broad market index, Ibovespa, fell almost 37% in the first quarter of 2020, while its financial index, IFNC, shrunk 38.6% in the same period. These numbers are slightly higher than the ones presented by Akhtaruzzaman *et al*. (2021) for S&P500 and FTSE100 indices. Furthermore, Brazil banking sector contains the best ranked banks of Latin American, in terms of total assets, with stocks traded in its stock market (B3), most of which compose the Ibovespa index[3].

Thus, we add to the discussion of the COVID-19 financial effects over Brazil. Our data set comprises daily returns of the IFNC index and of 19 bank stocks, and COVID-19 data of 7 localities and the world covering the period between January 29 and August 31, 2020. For our first exercise we follow Aguiar-Conraria *et al*. (2018) applying concepts as partial coherence and partial phase-difference to identify co-movements and lead-lag relationships between the financial index series and COVID-19 data. In the second exercise, we apply the same methods to investigate banking sector behavior during the pandemic.

We also follow Costa *et al*. (2021) in the use of Granger causality to draw a pass-through path between the banking stocks and to make a static comparative analysis considering these stocks before and after the pandemic. Forbes and Rigobon (2001) define contagion as a significant increase in cross-market links after a shock to an individual country (or a group of countries). Considering this definition, the Granger causality allied with the distance metric (Dissimilarity), approached in Aguiar-Conraria and Soares (2011), give us insights about contagion inside the sector. Also, following Wu *et al*. (2020) we compare the intensity of the co-movements between the banks in the presence and absence of the COVID-19.

[3] The banking sector had the biggest share (nearly 18%) of Ibovespa index composition at February 23, 2021.

This paper has the following layout: Section 2 provides a quick literature review; Section 3 presents the methodology; Section 4 contains a description of the employed dataset and presents the obtained results; finally, our final concluding remarks are discussed in Section 5.

2 BRIEF LITERATURE REVIEW

Concerning the discussion on financial integration and contagion, Rua and Nunes (2009) highlight the need of distinguishing the character of short and long-term relationships in the financial markets. For them, the short-run investor is focused on high frequency co-movements (short-term oscillations) while the long-run investor is interested in the opposite case. They assess the co-movements on the stock returns of the major developed countries and concentrate the analysis on aggregate and sectoral levels using the wavelet framework.

Da Silva *et al*. (2019) adds that this distinction between short and long-term allows to work complex systems with easier common features structures. They use a sample containing the financial sector indices of some of the G-20 economies from March 30, 2009, to December 31, 2013. Applying wavelet tools, they find significant coherency between the European core, idem for NAFTA countries partners. With respect to emerging economies group, they also find synchronization between Brazil and India, both BRIC members.

Still in this line, other papers contributes to this vast literature: Chen *et al*. (2012) and Matos, da Silva *et al*. (2021) assess the relationship between financial and business cycles through the co-movements between macro-finance, credit, and financial variables; Bekaert *et al*. (2005) and Gkillas *et al*. (2019) analyse, respectively, stock returns and equity market data in different regions of the world in order to provide insights about contagion during crisis scenarios. Focusing precisely on economic groups, Matos *et al*. (2016) investigates financial integration and contagion on BRIC members, and Rejeb and Boughrara (2015) focus the analysis on emerging and developing markets.

Bringing the debate to the banking sector, Kaufman (1994) lists some reasons why contagion is more likely to be serious in this sector compared to other industries. Basically, it happens faster, causing substantial number of other failures, but it also spreads beyond the sector boundaries resulting in considerable damage to the financial system and the macroeconomy as a whole.

Schoenmaker (1996) derives a test for bank failure and applies it to US economy, in the period from 1880 to 1936. The results confirm the presence of risk contagion at the time, reinforcing the role central bank should play in the banking regulation to prevent the serious effects inherent to bank failure.

Analysing banking contagion during the Global Financial Crisis, Dungey and Gajurel (2015) identify evidence on 45 out of 54 economies studied. They find that the idiosyncratic source of contagion raised by 37% the possibility of a systemic crisis and argue that the competent authorities should concern not only on the systematic type of contagion.

Some other works also study contagion in the bank industry (BOLTON; JEANNE, (2011); DUGGAR; MITRA, (2009); GABRIELI; SALAKHOVA, (2019); GROPP *et al*., (2009) and PAIS; STORK, (2011)).

In this perspective, our paper contributes giving some insights related to contagion by analysing the links between the banks and mapping the pass-through for the sector in the COVID-19 scenario in a large emerging market.

3 WAVELET FRAMEWORK

3.1 A Brief Review of Continuous Wavelet Transform

The Continuous Wavelet Transform turns an original function $y(t)$, which depends on time, into another one subjected now to time and frequency $w_y(\tau, s)$. According to Aguiar-Conraria and Soares (2018) the continuous wavelet transform is given by[4]

$$W_y(\tau, s) = \int_{-\infty}^{\infty} y(t) \frac{1}{\sqrt{|s|}} \bar{\omega} \left(\frac{\tau - s}{t}\right) dt \quad s, \tau \in \Re, s \neq \{0\} \tag{1}$$

where τ represents the wavelet localization in time and s stands for frequency. Precisely, $|s|$ denotes scale, and it has an inverse relation with frequency: if $|s| < 1$, then there is a low scale or a high frequency, being the opposite for the case where $|s| > 1$. The term $\bar{\omega}$ is the general wavelet form (Mother Wavelet), where the Morlet Wavelet, first introduced by Grossmann and Morlet (1984), is the most common complex-valued wavelet employed. In this study we follow most empirical literature and employ standard values, Morlet[5] and $\omega_0 = 6$.

[4] $\bar{\omega}$ represents the complex conjugation of the mother wavelet. The same idea applies to other overlined terms we present. For more details, see Aguiar-Conraria and Soares (2010).

[5] $\psi_{\omega_0}(t) = \pi^{-\frac{1}{4}} e^{i\omega_0 t} e^{-\frac{t^2}{2}}$.

3.2 Wavelet Tools

Given two time series, $y(t)$ and $x(t)$, the Wavelet Power Spectrum is defined as

$$WPS_i(\tau, s) = |W_i(\tau, s)|^2 , \qquad i = y, x \tag{2}$$

This measure works as a variance measure for the time/frequency plane.

The Cross-Wavelet Analysis comprehends concepts (namely as cross wavelet transform, cross-wavelet power, wavelet coherence and phase-difference) that enable us to handle analysis with two time series. The Cross-Wavelet Transform is given by the product of W_y and $\overline{W_x}$

$$\mathrm{W}_{\mathrm{yx}}(\tau, \mathrm{s}) = \mathrm{W}_{\mathrm{y}}\overline{W_x} \tag{3}$$

The same way one has the idea of variance in the univariate case, the Cross Wavelet Power depicts the local covariance between two time series

$$(XWP)_{yx} = |W_{yx}| \tag{4}$$

The Wavelet Coherence is denoted by

$$R_{yx}(\tau, s) = \frac{\left| S\left(W_{yx}(\tau, s)\right)\right|}{\sqrt{S\left(\left|W_y\right|\right)^2 S(|W_x|)^2}} \tag{5}$$

where $0 < R_{yx}(\tau, s) < 1$, and S is a smooth operator for scale and time.

For analysing a lead-lag relationship between $y(t)$ and $x(t)$, one can use the Phase-Difference

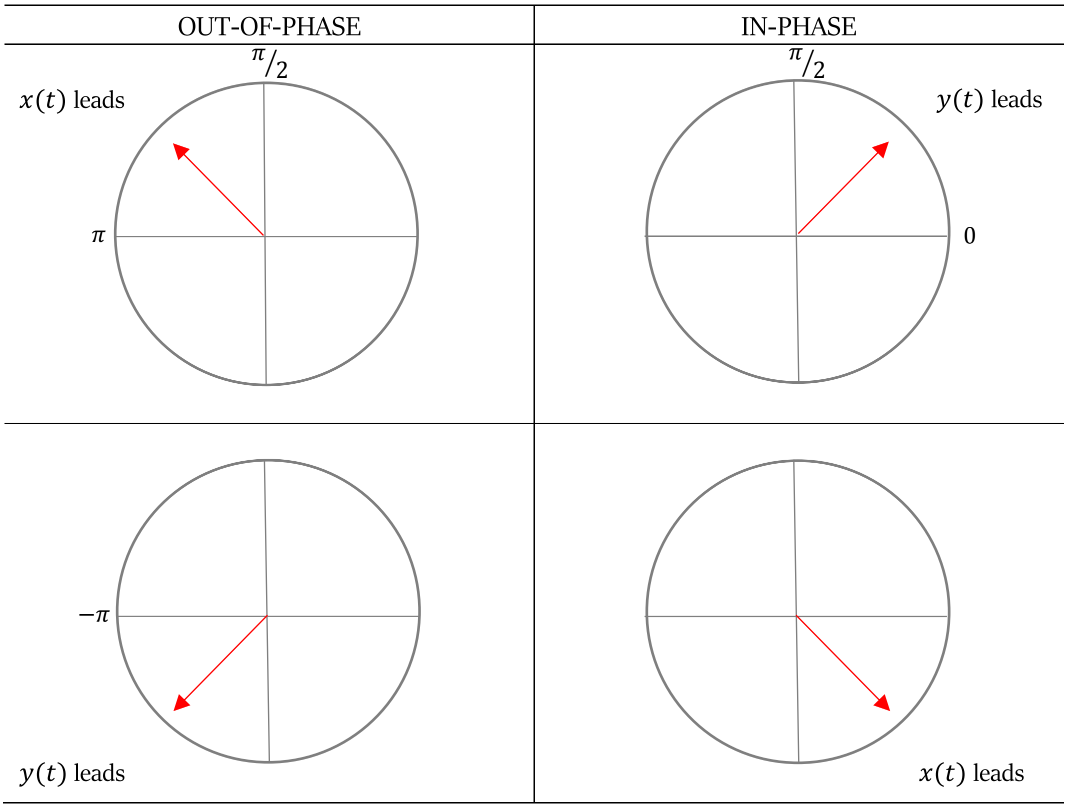
$$\phi_{y,x}(\tau, s) = \tan^{-1}\left(\frac{\Im(\mathrm{W}_{\mathrm{yx}})}{\Re(\mathrm{W}_{\mathrm{yx}})}\right) \tag{6}$$

where $\Re(.)$ and $\Im(.)$ are the real and imaginary parts of W_{yx}. The Phase-Difference allows us to obtain information about delays between two series, pointing which one was leading and which one was lagging in a specific time window.

The phase-difference ranges from $-\pi$ to π, and depending on the signal and value it has, one can have different meanings. If $\phi_{y,x}$ is null, $y(t)$ and $x(t)$ move together for a specific time-frequency. In case $\phi_{y,x} \epsilon \left(0, \frac{\pi}{2}\right)$, $y(t)$ leads in-phase. Conversely, $\phi_{y,x} \epsilon \left(-\frac{\pi}{2}, 0\right)$ indicates $x(t)$ leads in-phase. A phase-difference of $\phi_{y,x} = \pm\pi$ means anti-phase relation with series moving in opposite direction. If $\phi_{y,x} \epsilon \left(-\pi, -\frac{\pi}{2}\right)$ there is an anti-phase relation with

$y(t)$ leading, while if $\phi_{y,x} \epsilon \left(\frac{\pi}{2}, \pi\right)$ there is an anti-phase relation in which $x(t)$ leads. We follow Sharif *et al*. (2020) in the use of arrows to a better description of lead-lag roles played by $y(t)$ and $x(t)$. Arrows turned left indicate anti-phase relationship: if turned up-left means $x(t)$ leads while if turned down-left $y(t)$ leads. Arrows turned right mean in-phase relationship: if pointed-up $y(t)$ leads and if pointed-down $y(t)$ follows $x(t)$.

Figure 1: Phase-Difference arrows definition.



According to Aguiar-Conraria and Soares (2011), given a pair of wavelet spectra standing for $y(t)$ and $x(t)$, the Dissimilarity between them is measured as

$$dist(W_y, W_x) = \frac{\sum_{k=1}^{K} w_k^2 \left[d\left(l_x^k, l_y^k\right) + d(u_k, v_k)\right]}{\sum_{k=1}^{K} w_k^2} \tag{7}$$

where w_k^2 are the weights equal to the squared covariance explained by each axis, l_x^k and l_y^k are leading patterns and u_k and v_k are singular vector satisfying variational properties. We adopt $K = 3$ for all computations of dissimilarities.

Considering our purposes, we intend to discuss the synchronism between the pairs index/COVID-19 or bank/bank assuming the presence of other related variables in the period. This means we verify the relationship between $y(t)$ and $x(t)$ after controlling for a vector of instruments $z(t)$. Following Aguiar-Conraria *et al*. (2018), the Complex Partial Wavelet Coherence is defined as

$$\xi_{yx,z} = \frac{\xi_{yx}-\xi_{yz}\overline{\xi_{xz}}}{\sqrt{(1-R_{yz}^2)(1-R_{xz}^2)}} \qquad (8)$$

Analogue to (5) and (6), the absolute value and the angles of $\xi_{yx,z}$ are, in this order, the Partial Coherence and Partial Phase-Difference.

4 DATA AND EMPIRICAL RESULTS

4.1 Data and Preliminary Analysis

Our data consists in a daily frequency sample, covering the period between January 29 and August 31, and is divided in two parts: health data set and financial data set.

The health data set comprises COVID-19 numbers of deaths and cases in some of most affected countries in the period: Brazil, France, Italy, United Kingdom and United States. Data from China and Hubei province also compose our sample in order to analyse the early stages of the pandemic. World data is also considered. As our final explanatory variable[6], we use daily log growth rate of 7-days moving average of new cases and deaths, based on Ding *et al*. (2020). This transformation accounts for weekends, holidays, week seasonality and outliers. The data source is the Center for Systems Science and Engineering (CSSE) at Johns Hopkins University (JHU).

The financial data set is composed by daily returns of the IFNC index and 19 banks. The banking stocks were selected, after following a filtering process, where we took only stocks which had at least 75% presence on trading days and removed repeated stocks of the same bank, prioritizing the common stock type over the preferred one[7] . For the IFNC index, the data source is the Brazilian stock market (B3) website. Bank stock prices were obtained from Economatica.

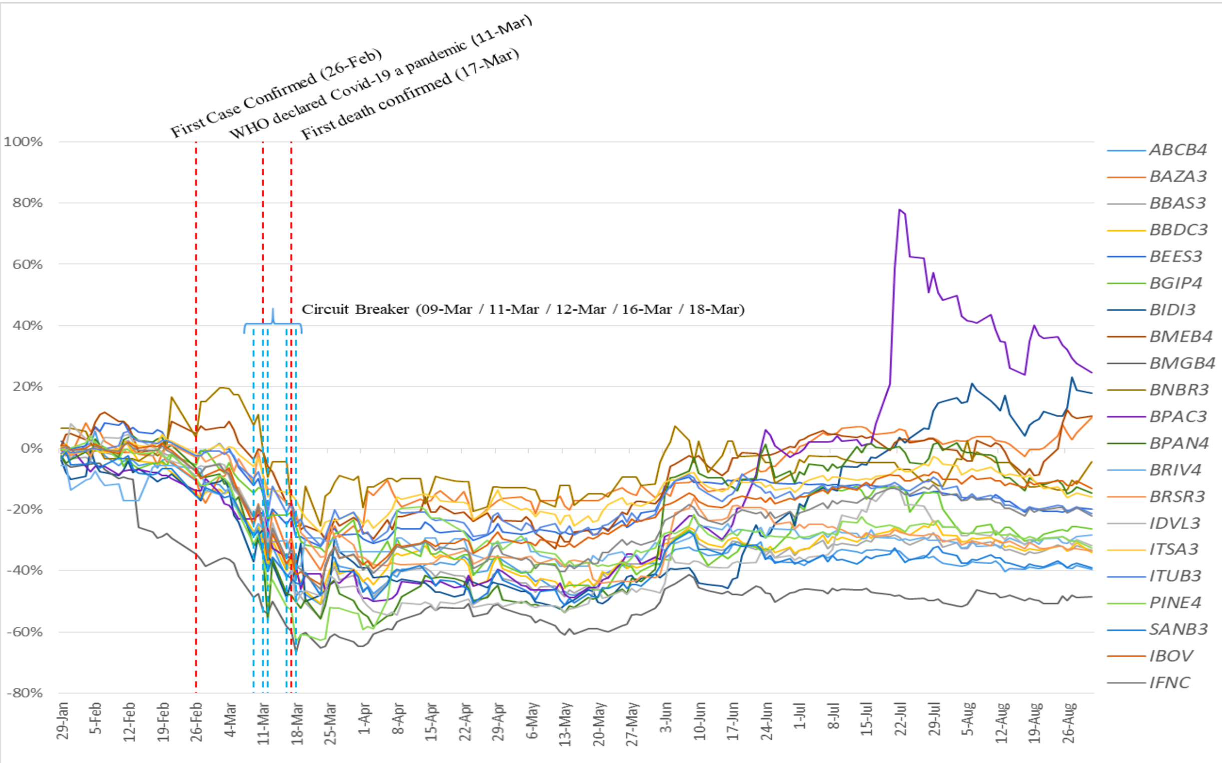
Figure 2.a shows the cumulative returns in the period, most part of considerable losses. The largest drawdown was recorded by BMGB4 and only four stocks had positive cumulative returns: BAZA3, BIDI3, BMEB4 and BPAC3. Considering the period from mid-February to

[6] The log growth rate of 7-days moving average is given by: $r_t = ln(1 + MA_7(x_t)) - ln(1 + MA_7(x_{t-1}))$, where $MA_7(x_t)$ and x_t stand, respectively, for 7-days moving average and daily number of cases/deaths.
[7] Basically, the Brazilian stocks are classified as common and preferred, where these receive, respectively, the numbers 3 and 4 in its ticker symbol. There are some other classes (and respectively numbers) according to the voting rights they imply.

late-March, the returns suffered considerable slump and it is worth noting some events in Brazil that occurred at this period, either related to COVID-19 or associated to its stock market: i) first case confirmed (26-Feb), ii) World Health Organization declared COVID-19 a pandemic (11-Mar), iii) first death confirmed (17- Mar), iv) circuit breaker (09-Mar, 11-Mar, 12-Mar, 16-Mar and 18-Mar). After this free fall period, there are two other moments: a stabilization period that begins from early-April and lasts until late-May, and an apparent-recovering period starting from early-June. Concerning number of cases of COVID-19 (Figure 2.b), it looks like some locations have reached the peak and then started decreasing (China and Hubei) while others, after a decreasing period, the growth rate started raising again (France, Italy and UK). Brazil and US seem to be in a stable moment after a huge increase in the number of cases. In terms of number of deaths (Figure 2.c), it appears that some locations have reached its peak and then declined (France and Italy), some with punctual increases followed by a new reduction (China, Hubei and Italy). Again Brazil and US appear to be stable by the end of the period.

Figure 2: Cumulative returns on banks and IFNC and Ibovespa indices, and COVID-19 numbers worldwide.

a) Cumulative Returns



Notes: Data from January 29 to August 31, 2020. Source: Economatica, B3 and Johns Hopkins Corona Virus Research Center.

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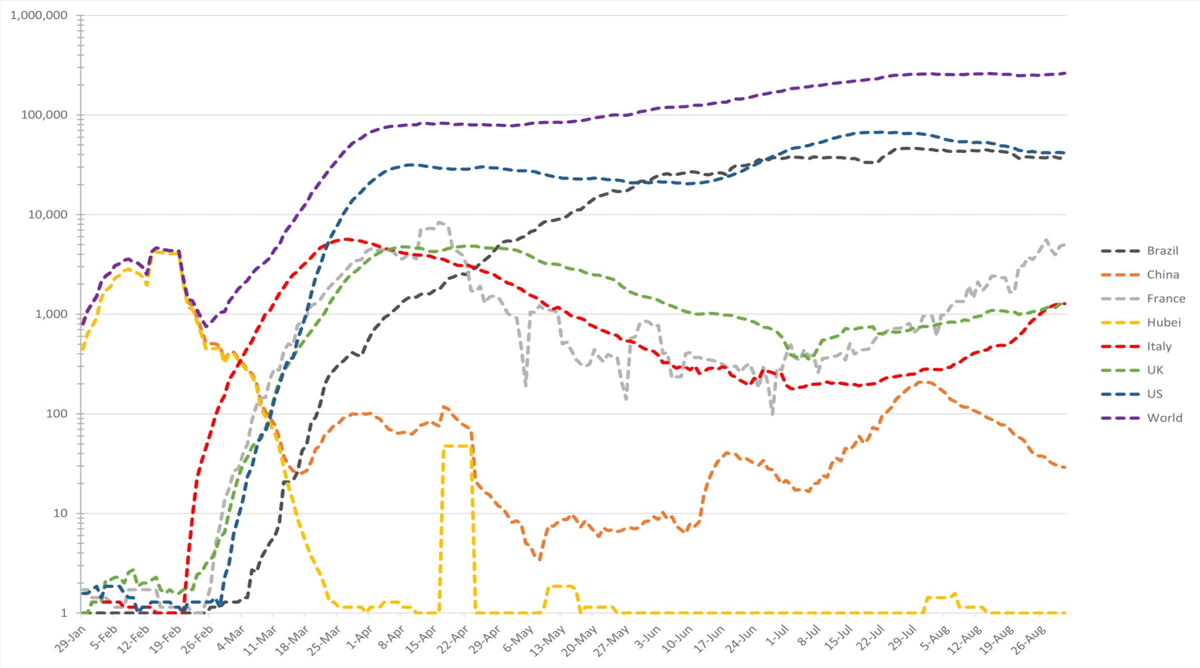
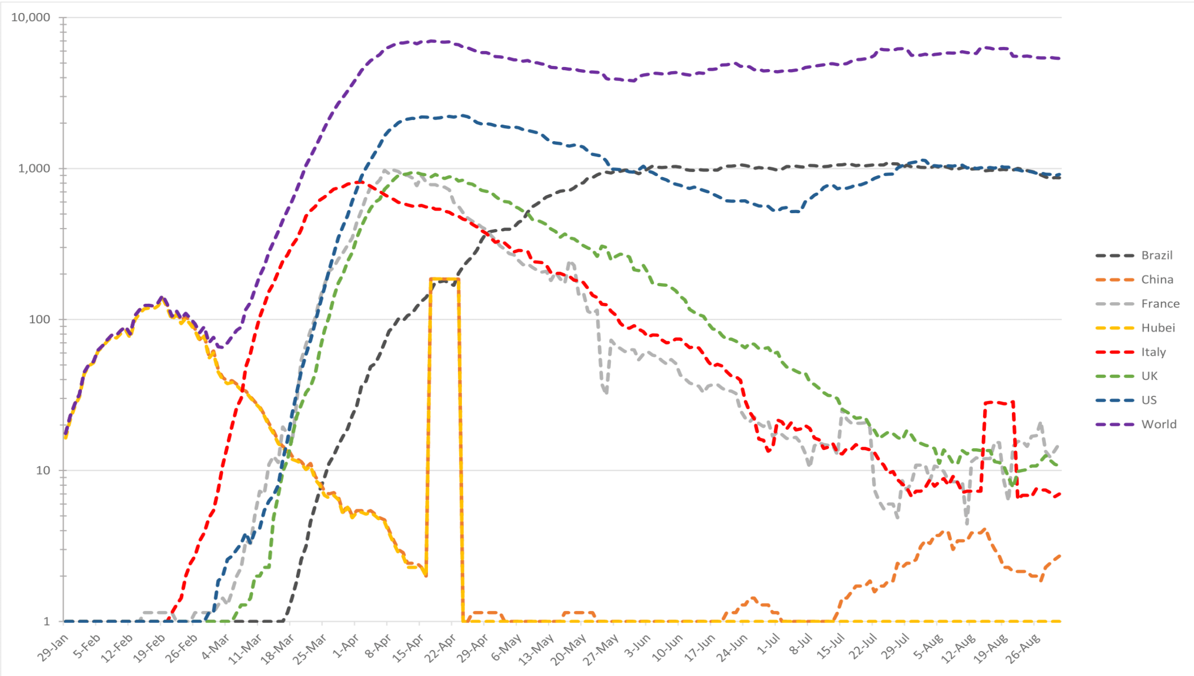
Figure 2: Cumulative returns on banks and IFNC and Ibovespa indices, and COVID-19 numbers worldwide.

b) Moving Average: Daily Cases



c) Moving Average: Daily Deaths



Notes: Data from January 29 to August 31, 2020. Source: Economatica, B3 and Johns Hopkins Corona Virus Research Center.

Table 1: Brazilian stock and financial markets and Covid-19 numbers worldwide.

		COVID-19 Variables															
		Deaths								Cases							
		Brazil	China	France	Hubei	Italy	UK	US	World	Brazil	China	France	Hubei	Italy	UK	US	World
Panel A: Dissimilarities																	
IFNC		0.38*	0.28*	0.40	0.28*	0.39*	0.38*	0.34**	0.40	0.37*	0.41	0.41	0.39	0.27***	0.38*	0.32***	0.29**
Panel B: Granger Causalities																	
IFNC	Covid → Index	0.00	0.62	0.36	0.66	0.01	0.09	0.05	0.82	0.01	0.01	0.87	0.04	0.00	0.04	0.00	0.60
	Index → Covid	0.01	0.41	0.38	0.43	0.71	0.22	0.01	0.40	0.00	0.70	0.49	0.34	0.12	0.59	0.00	0.47
Panel C: Coronavirus statistics																	
Lethality (Deaths to cases)		3.11%	5.25%	10.09%	6.62%	13.18%	12.36%	3.04%	3.34%								
Mortality (Deaths per million inhabitants)		570.0	3.3	466.9	75.5	587.1	610.5	553.8	108.8								
Total Deaths (Thousands)		121.4	4.7	30.5	4.5	35.5	41.5	183.6	850.5								
Mean (Daily log growth - 7 days m.a.)		3.13%	-0.92%	1.26%	-1.36%	0.90%	1.10%	3.16%	2.60%	4.91%	-1.53%	3.73%	-2.89%	3.31%	3.33%	4.67%	2.68%
S.D. (Daily log growth - 7 days m.a.)		6.97%	48.10%	22.20%	47.78%	17.51%	11.45%	9.41%	7.74%	11.26%	18.38%	29.54%	40.14%	15.36%	11.42%	13.43%	9.48%

Notes: [a] Data from January 29 to August 31, 2020. [b] Dissimilarities between IFNC and the explanatory variables (deaths and deaths). [c] The p-values are derived from Monte Carlo simulations with 5.000 runs tanking red noise as null hypothesis: * stands for $p < 10\%$, ** for $p < 5\%$ and *** for $p < 1\%$. [d] Granger causality tests take only one IFNC lag as dependent variable. Source: Economatica, B3 and Johns Hopkins Corona Virus Research Center.

Table 1 (Panel A) contains the dissimilarities between IFNC index and the COVID-19 cases and deaths. Almost all localities series have significant results, indicating co-movement between the index and COVID-19 numbers, which we highlight Brazil, Italy, UK and US COVID-19 series. In Table 1 (Panel B) we report the Granger causality tests. Deaths and cases in Brazil, Italy, UK and US along with the number of cases in China and Hubei have predictive power over IFNC. On the other hand, the index can only anticipate deaths and cases in Brazil and US. Some COVID-19 statistics are displayed in Table 1 (Panel C).

4.2 IFNC vs COVID-19

These previous results lead to our first wavelet analysis, in which we investigate how one day earlier COVID-19 info relate with the Brazilian financial index, IFNC. Considering all COVID-19 series we dispose, there are 16 resultant pairs presented in Figure 3 displaying the partial wavelet coherence given by a heat-map with two dimensions (frequency and time), which ranges from blue (small coherence) to red (high coherence), and the V-shaped black line represents the cone of influence. Following Sharif *et al*. (2020), we implement the use of phase arrows in order to have a more accurate picture of the co-movements in the period.

Chronologically, due to the first cases and deaths recorded in China, one can notice a first significant area dating from the beginning of the second fortnight of February involving the Brazilian banking sector, through IFNC, and both cases and deaths in Hubei and also deaths in China. This coherency area is interesting for being a high frequency type (2 days), although directionless and with undefined leadership. This suggests something in the air, but inconclusive. Aggregating cases and deaths worldwide still in February, it is possible to state the same thing. In short, mainly there is a coherency between IFNC and deaths in Asia, despite the lack of direction and leadership.

Mid-March we evidence significant coherency areas of high frequency associated to both cases in France and Italy, again inconclusive ones, however in the same period the first cases in Brazil, US cases and France deaths are the first to suggest the presence of a high frequency anti-phase leadership of these variables over the Brazilian financial index.

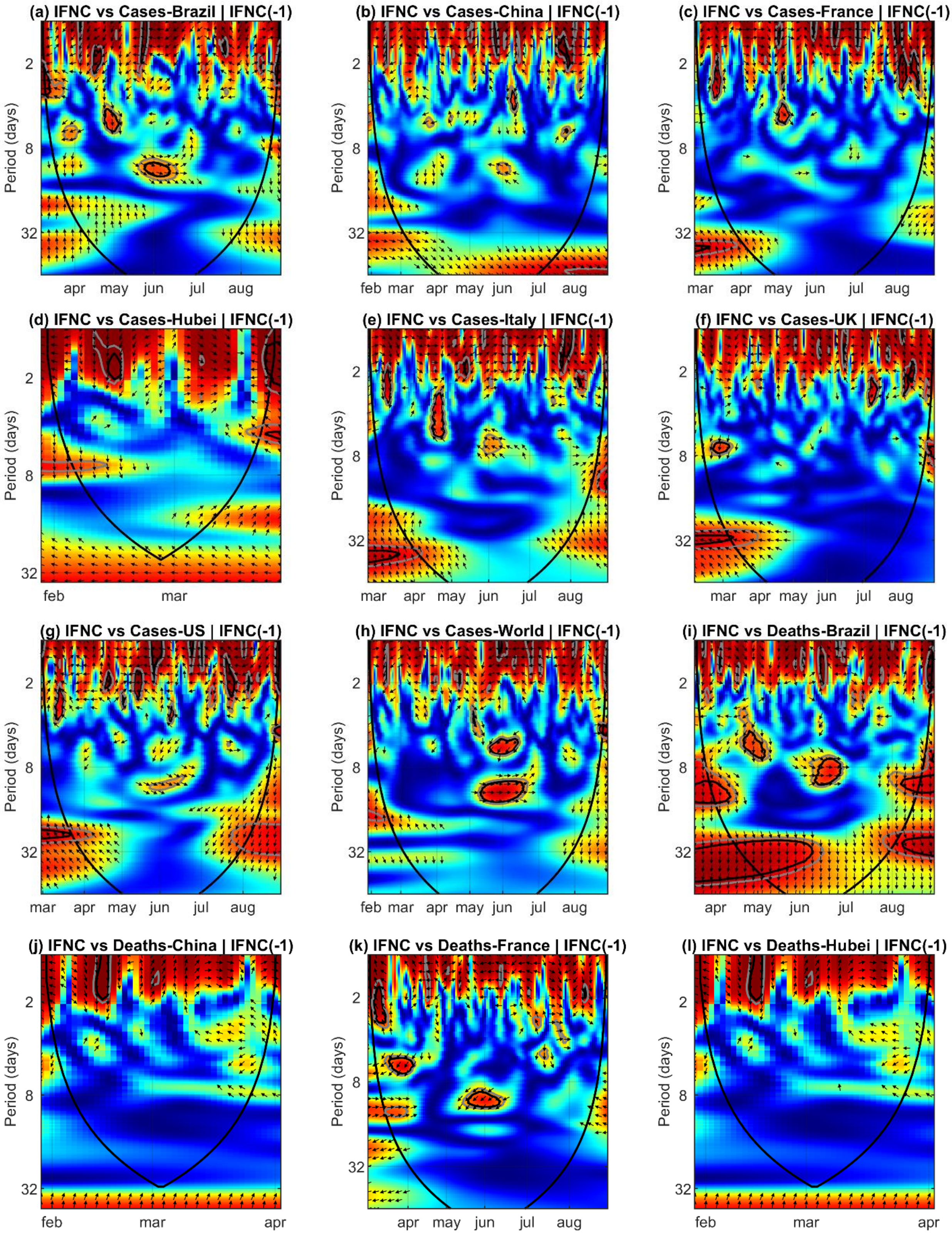
During almost the whole second half of April, it is timely note that the cycles of cases in Italy started to lead in opposite and intuitive direction the business cycle of the Brazilian banking sector, while it is curious the evidence that these sectorial Brazilian cycles are leading the cycle of cases in its own country. That means a forward-looking behavior of the Brazilian stock market, banking sector, foreseeing through the drop of its own returns the considerable rise of cases that was to come.

In May there is a predominance of anti-phase coherences of high frequency involving IFNC and Brazil and US cases and deaths in Italian soil. Still there is a significant coherency of low frequency kind, but inconclusive, associating the sectorial index and deaths in Brazil during the period between early May and early June.

Considering now June, it is informative that the cycles of 8 days show coherencies able to suggest that the Brazilian banking sector was anticipating through its own performance recovering moment the decline of deaths in French soil. Although, it is atypical and not very intuitive to note a phasic coherence (8 days frequency) between the IFNC and Brazil deaths in this same month.

In the second semester, we call attention to the leadership power, intuitively anti-phasic, of the high frequency cycles considering the cases in France and the deaths in US.

Figure 3: Partial wavelet coherence IFNC vs COVID-19 controlled by lagged IFNC.



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 null hypothesis. [b] Data from January 29 to August 31, 2020. Source: Economatica, B3 and Johns Hopkins Corona Virus Research Center.

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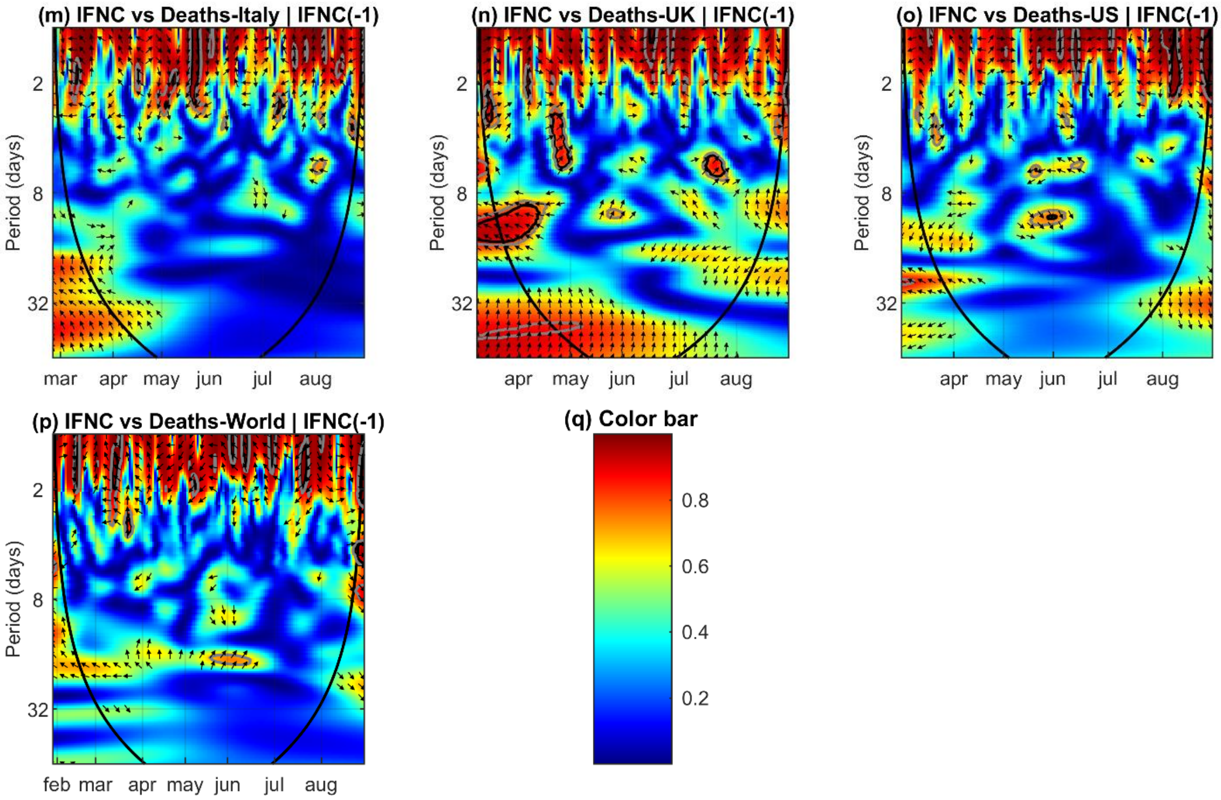
Figure 3: Partial wavelet coherence IFNC vs COVID-19 controlled by lagged IFNC.



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 null hypothesis. [b] Data from January 29 to August 31, 2020. Source: Economatica, B3 and Johns Hopkins Corona Virus Research Center.

4.3 Banking Stocks Relationships

A second intent in this study is to evaluate the behavior of the banking sector during the pandemic. We assess the Granger causality test based on VAR between the selected bank stocks, controlled by lagged IFNC and Ibovespa. Compared to 2019, the number of significant Granger causalities in 2020 is larger (Table 3 – Panel B), indicating a lining up between the banks during the pandemic. We highlight the increase of the unidirectional and bidirectional pairs from, respectively, 27 to 42 and 3 to 11[8] in 2020, and the fact that BPAN4 is the stock who mostly Granger causes. This rise of links inside banking sector is also supported by the dissimilarities, whose number of significant pairs also increased in 2020 (Table 3 – Panel C). We find an average reduction of 25%, with only 15 out 153 available pairs[9] recording increase

[8] Only the pair ITUB3 x SANB3 was significant in both years.
[9] We refer to available pairs because all combinations involving BMGB4 are discarded, once this stock was not actively trading in 2019 (more than 30 trading consecutive days).

in dissimilarity. The pairs ITSA3 x PINE4 and IDVL3 x PINE4 have, respectively, the maximum percentage decrease (near -64%) and increase (65.3%) in dissimilarity.

Even though we can make use of the Granger causality tool, we have the issue of having way too many significant combinations, what makes very hard to draw a pass-through path inside the sector. We decided then to pick only those significant pairs which are also significant at the dissimilarities, standing a total of 13 stocks. By doing this we focus on the core of relations, in order to have a clearer environment to trace a pass-through path. Considering this restricted scenario (Figure 4), it is still difficult to identify an evident pathway, but we raise attention to an interesting aspect: ITSA3 is the starting point causing BPAN4, BRSR3 and ITUB3. Also, we note that BPAN4 can be seen as a catalyst once it Granger causes 8 stocks in total. The rest of the relationships occurs next, in a second plan.

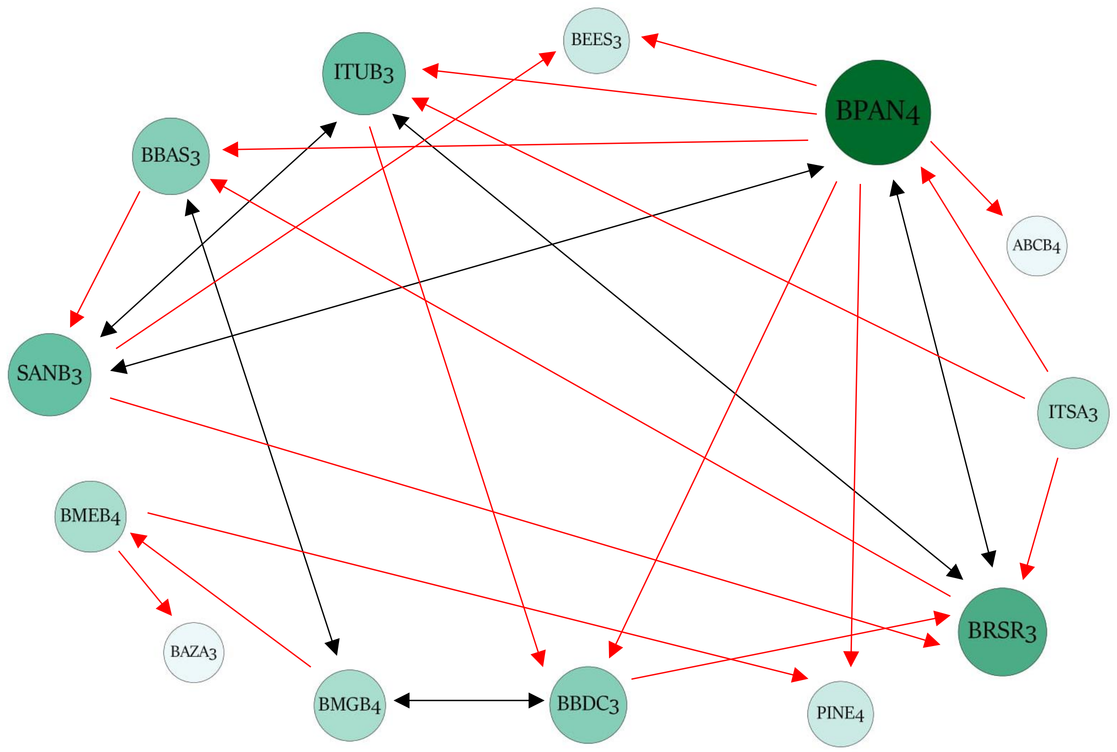
We emphasize the fact that ITSA3 represents shares of *Itaúsa*, a conglomerate that holds companies in different sectors, like shoe industry, natural gas transportation industry, but especially it controls the *Itaú*, which is the biggest bank in Latin America[10]. In the same line, the *Banco Pan*, which detains BPAN4 shares, is controlled by *Caixa Econômica Federal*, who is the third biggest bank in Latin America, and *BTG Pactual*, the biggest investment bank of Latin America. Another facts about *Banco Pan* is that it acts in different areas as digital bank and was performing considerably well[11] before the pandemic. It also stands out with highest volatility, highest negative and positive daily variation, and also the highest semivariance and market beta during the crisis, as can be seen in Table 3 (Panel A). These points can help to explain why ITSA3 plays the initial point role and BPAN4 acts as a catalyst in the banking sector pass-through. It is worth noting that, as mentioned before, according to Ding *et al*. (2020), companies with robust finances in 2019 experienced milder negative oscillations in its stock prices. This result applies to ITSA3 case[12]: it has the second smallest oscillation (in terms of S.D), the smallest range between maximum and minimum daily return, the smallest semivariance risk metric and the smallest absolute drawdown.

We deepen the analysis for further insights about the financial effects. We follow Wu *et al*. (2020) in order to see the COVID-19 effects (represented by US cases and Italy deaths) in the relationships among the bank shares. Put in other words, the idea is to exclude any influence of COVID-19 in banking sector by calculating Partial Wavelet Coherence and

[10] Approximately 406.31 US$B in terms of total assets in 2019.
[11] BPAN4 has appreciated an increase of nearly 450% in 2019.
[12] Despite negative cash increase of 12 US$ million in 2019, the total assets were over 16.7 US$B and the liabilities stood only a small share (roughly 2.3 US$B) of the total liabilities and stockholders' equity (nearly 16.75 US$B) for the same period.

comparing to the Wavelet Coherence. Again there are too many pairs to investigate, then we choose only the pairs with bidirectional Granger causality. We find that 10 out of 11 pairs have a percentage reduction in the significant areas (Figure 5), with an average reduction in the magnitude of 37%. The pair BBDC3 x BMGB4 has the highest reduction (-68%), while the pair BPAN4 x BRSR3 detains the only increase (roughly 9%) of the set. Overall, the results suggest COVID-19 info plays a key role in the co-movements of Brazilian banking sector in 2020.

Figure 4: Banking sector pass-through during the pandemic.



Note: [a] Red and black arrows are for, respectively, unidirectional and bidirectional causality. [b] Darker colors have more links while lighter ones have less links.

Table 2: Summary statistics of banks and IFNC index.

	Statistics							
	Cumulative Returns	**Mean**	**S.D.**	**Min.**	**Max.**	**Market Beta**	**Semivariance**	**Max. Drawdown**
ABCB4	-39.96%	-0.27%	3.72%	-14.97%	17.09%	0.90	2.72%	-50.65%
BAZA3	7.80%	0.14%	4.34%	-15.11%	15.75%	0.92	3.01%	-39.63%
BBAS3	-33.82%	-0.16%	4.77%	-16.69%	17.13%	1.25	3.35%	-54.63%
BBDC3	-34.24%	-0.20%	4.20%	-14.35%	16.33%	1.11	2.89%	-49.91%
BEES3	-20.57%	-0.13%	**2.27%**	-10.92%	6.04%	0.53	1.74%	-33.67%
BGIP4	-26.42%	-0.12%	4.13%	-12.04%	13.79%	0.49	2.90%	-46.15%
BIDI3	17.97%	**0.28%**	5.75%	-27.18%	25.39%	0.71	4.03%	-50.5%
BMEB4	10.06%	0.12%	3.19%	-11.20%	8.91%	0.40	2.17%	-33.31%
BMGB4	**-48.53%**	**-0.34%**	4.48%	-17.58%	16.76%	0.83	3.37%	**-65.66%**
BNBR3	-10.35%	0.04%	4.86%	-14.87%	17.28%	0.49	3.41%	-29.89%
BPAC3	**24.67%**	0.27%	5.01%	-11.85%	31.11%	**0.23**	2.96%	-50.07%
BPAN4	-12.49%	0.14%	**6.90%**	**-33.64%**	**46.30%**	**1.53**	**4.44%**	-57.13%
BRIV4	-24.18%	-0.13%	3.43%	-9.29%	15.23%	0.24	2.26%	-35%
BRSR3	-33.48%	-0.22%	3.42%	-9.03%	16.52%	0.43	2.20%	-44.01%
IDVL3	-32.97%	-0.17%	4.33%	-18.18%	17.24%	0.76	3.13%	-54.27%
ITSA3	-16.11%	-0.09%	2.33%	**-7.78%**	**5.79%**	0.47	**1.70%**	**-27.81%**
ITUB3	-20.69%	-0.11%	3.13%	-10.08%	11.03%	0.77	2.23%	-30.52%
PINE4	-30.69%	-0.09%	5.74%	-21.94%	30.43%	1.09	3.47%	-63.04%
SANB3	-38.62%	-0.24%	4.27%	-12.60%	18.58%	0.94	2.94%	-49.5%
IFNC	-23.04%	-0.11%	3.65%	-13.28%	13.15%	1	2.61%	-45.98%

Notes: [a] The highest and lowest value of each metric are highlighted in bold. [b] The market beta metric was calculated using Ibovespa as the market index.

Table 3: Dissimilarities and Granger Causality.

Panel A: Dissimilarities and Granger causality between IFNC index and banks

Indexes		**ABCB4**	**BAZA3**	**BBAS3**	**BBDC3**	**BEES3**	**BGIP4**	**BIDI3**	**BMEB4**	**BMGB4**	**BNBR3**	**BPAC3**	**BPAN4**	**BRIV4**	**BRSR3**	**IDVL3**	**ITSA3**	**ITUB3**	**PINE4**	**SANB3**
IFNC	2019	0.35	0.48	**0.23*****	**0.20*****	0.39	0.49	0.55	0.49	-	0.53	0.61	0.34	0.57	0.39	0.72	**0.27****	**0.20*****	0.50	0.34
	2020	**0.23****	0.39	**0.15*****	**0.11*****	**0.23****	0.42	0.49	**0.30***	**0.27****	0.39	0.36	**0.27***	0.31	**0.24****	0.40	**0.19*****	**0.19*****	**0.23*****	**0.23****
IFNC	Row → Column	0.21	0.13	0.81	0.75	0.74	0.37	0.22	0.96	-	0.36	0.33	**0.10**	0.66	**0**	0.66	0.13	**0.07**	0.68	**0**
(2019)	Column → Row	0.25	0.31	0.76	0.37	0.44	0.97	0.33	0.40	-	1	**0.03**	0.41	0.29	0.19	0.29	0.17	0.90	0.16	0.43
IFNC	Row → Column	0.69	0.43	0.21	0.16	0.91	0.39	**0**	**0**	**0**	0.34	**0.05**	**0.03**	0.15	0.13	0.67	0.44	0.46	0.69	0.10
(2020)	Column → Row	0.94	**0.01**	0.49	0.50	0.61	0.63	**0**	0.46	**0**	0.64	0.92	**0**	0.51	**0.04**	**0.07**	**0.05**	0.28	0.10	0.23

Notes: [a] The Granger causalities and dissimilarities were calculated considering the periods may to December, 2019, and January to august, 2020. [b] Considering the 2019 period, BMGB4 did not have a robust return series (more than 30 consecutive days), thus for some of the analysis there are no tabulated values. [c] The p-values are derived from Monte Carlo simulations with 5.000 runs tanking red noise as null hypothesis: * stands for $p < 10\%$, ** for $p < 5\%$ and *** for $p < 1\%$. [d] For Granger causalities tests, the unconditional VAR was used for the combinations index versus bank while for the combinations bank versus bank the conditional VAR was implemented, tanking Ibovespa and IFNC as control variables, both lagged. [e] The blue and red colour stand, respectively, for unidirectional and bidirectional Granger causality.

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Table 3: Dissimilarities and Granger Causality.

Panel B: Granger causality between banks. Obs: Bank (row) causes bank (column)

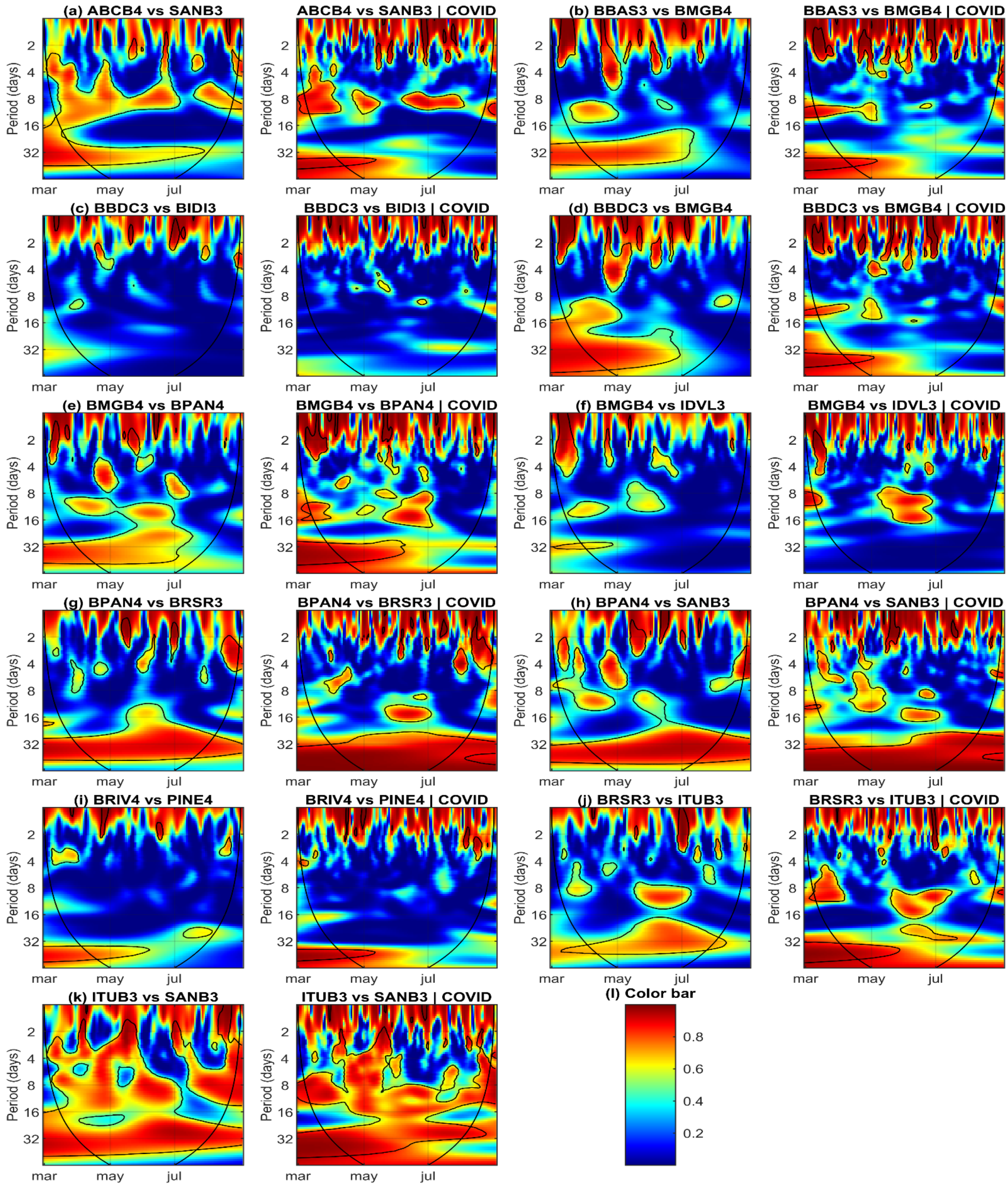
(2019) Banks	ABCB4	BAZA3	BBAS3	BBDC3	BEES3	BGIP4	BIDI3	BMEB4	BMGB4	BNBR3	BPAC3	BPAN4	BRIV4	BRSR3	IDVL3	ITSA3	ITUB3	PINE4	SANB3
ABCB4		0.83	0.61	0.06	0.89	0.42	0.18	0.05	-	0.30	0.90	0.77	0.11	0	0.27	0.03	0.08	0.67	0
BAZA3	0.12		0.32	0.56	0.38	0.30	0.69	0.11	-	0.03	0.15	0.06	0.68	0.25	0.57	0.70	0.96	0.04	0.22
BBAS3	0.33	0.10		0.68	0.64	0.31	0.73	0.83	-	0.08	0.01	0.02	0.35	0	0.23	0.72	0.37	0.97	0
BBDC3	0.34	0.14	0.81		0.59	0.71	0.30	0.96	-	0.24	0.22	0.04	0.62	0	0.99	0.03	0.10	0.99	0
BEES3	0.09	0.32	0.29	0.24		0.41	0.87	1.00	-	0.06	0.66	0.02	0.97	0.18	0.21	0.90	0.74	0.33	0.42
BGIP4	0.85	0.73	0.77	0.76	0.65		0.93	0.86	-	0.62	0.63	0.81	0.75	0.01	0.71	0.91	0.58	0.02	0.95
BIDI3	0.06	0.30	0.53	0.61	0.98	0.36		0.67	-	0.01	0.06	0.25	0.08	0.82	0.08	0.06	0.16	0.02	0.96
BMEB4	0.87	0.44	0.74	0.94	0.44	0.19	0.93		-	0.32	0.98	0.59	0.83	0.27	0.91	0.31	0.13	0.13	0.88
BMGB4	-	-	-	-	-	-	-	-		-	-	-	-	-	-	-	-	-	-
BNBR3	0.53	0.83	0.82	0.47	0.46	0.70	0.20	0.81	-		0.82	0.01	0.16	0.19	0.88	0.61	0.61	0.39	0.61
BPAC3	0.93	0.94	0.07	0.23	0.85	0.37	0.77	0.36	-	0.61		0.63	0.89	0.02	0.72	0.73	0.46	0.69	0.85
BPAN4	0.61	0.45	0.14	0.30	0	0.33	0.43	0.29	-	0.84	0.33		0.35	0.19	0.10	0.83	0.15	0.65	0.35
BRIV4	0.23	0.65	0.17	0.44	0.97	0.81	0.78	0.32	-	0.68	0.29	0.57		0.56	0.65	0.32	0.13	0.87	0.35
BRSR3	0.76	0.91	0.65	0.24	0.56	0.14	0.52	0.65	-	0.41	0.62	0.81	0.29		0.59	0.37	0.32	0.78	0.34
IDVL3	0.41	0.87	0.36	0.06	0.97	0.30	0.99	0.50	-	0.62	0.60	0.90	0.58	0.87		0.59	0.26	0.83	0.64
ITSA3	0.79	0.91	0.55	0.21	0.38	0.26	0.18	0.59	-	0.58	0.51	0.37	0.21	0	0.81		0.06	0.19	0
ITUB3	0.55	0.44	0.59	0.83	0.68	0.97	0.69	0.88	-	0.53	0.33	0.02	0.91	0	0.97	0.08		0.59	0
PINE4	0	0.04	0.20	0.15	0.01	0.39	0.85	0.08	-	0.66	0.01	0.69	0.16	0.74	0	0.34	0		0.70
SANB3	0.98	0.92	0.34	0.28	0.97	0.66	0.66	0.87	-	0.90	0.12	0.91	0.28	0.06	0.52	0.49	0.02	0.26	
(2020) Banks	**ABCB4**	**BAZA3**	**BBAS3**	**BBDC3**	**BEES3**	**BGIP4**	**BIDI3**	**BMEB4**	**BMGB4**	**BNBR3**	**BPAC3**	**BPAN4**	**BRIV4**	**BRSR3**	**IDVL3**	**ITSA3**	**ITUB3**	**PINE4**	**SANB3**
ABCB4		0.32	0.56	0.55	0.52	0.34	0.86	0.37	0.13	0.29	0.11	0.84	0.27	0.66	0.71	0.83	0.66	0.40	0.04
BAZA3	0.08		0.01	0.03	0.12	0.53	0.76	0.83	0.29	0.41	0.18	0.24	0.18	0.11	0.10	0.02	0.10	0.07	0.01
BBAS3	0.26	0.66		0.94	0.93	0.36	0.67	0.18	0.02	0.52	0.13	0.08	0.73	0.24	0.75	0.88	0.16	0.93	0.04
BBDC3	0.29	0.75	0.64		0.79	0.56	0	0.50	0.04	0.96	0.22	0.07	0.57	0.04	0.81	0.97	0.11	0.59	0.87
BEES3	0.82	0.08	0.77	0.93		0.50	0.56	0.28	0.23	0.82	0.03	0.35	0.21	0.05	0.66	0.43	0.76	0.26	0.19
BGIP4	0.75	0.03	0.71	0.62	0.60		0.36	0.57	0.32	0.83	0.36	0.31	0.61	0.65	0.77	0.87	0.30	0.35	0.49
BIDI3	0.87	0.91	0.02	0	0.20	0.41		0.92	0.06	0.37	0.58	0.20	0.40	0.75	0.23	0.38	0.01	0.52	0.67
BMEB4	0.99	0.03	0.47	0.24	0.42	0.62	0.34		0.81	0.10	0.25	0.54	0.35	0.99	0.91	0.10	0.81	0.03	0.19
BMGB4	0.28	0.53	0	0	0.33	0.07	0.01	0		0.02	0.01	0	0.07	0.46	0.01	0.69	0.81	0.62	0
BNBR3	0.28	0.16	0.62	0.69	0.59	0.54	0.66	0.08	0.29		0.05	0.70	0.73	0.99	0.31	0.28	0.97	0.40	0.04
BPAC3	0.22	0.16	0.23	0.42	0.23	0.22	0.17	0.73	0.11	0.51		0.91	0.46	0.62	0.14	0.71	0.59	0.39	0.22
BPAN4	0.03	0	0	0	0	0.75	0.08	0.49	0	0.76	0.29		0.68	0	0.42	0.13	0.02	0	0.03
BRIV4	0.67	0.13	0.74	0.51	0.69	0.71	0.34	0.55	0.17	0.67	0.46	0.81		0.10	0.98	0.18	0.21	0.01	0.40
BRSR3	0.85	0.77	0.02	0.66	0.95	0.02	0.04	0.02	0.35	0.56	0.07	0.01	0.59		0.43	0.32	0.03	0.33	0.46
IDVL3	0.28	0.07	0.17	0.05	0.10	0.72	0.06	0.42	0.01	0.44	0.07	0.52	0.37	0.80		0.10	0.10	0.01	0.21
ITSA3	0.10	0.89	0.31	0.18	0.16	0.26	0.28	0.53	0.89	0.61	0.03	0.05	0.54	0.04	0.03		0	0.28	0.90
ITUB3	0.47	0.22	0.08	0.04	0.97	0.18	0.55	0.12	0.24	0.39	0.03	0.21	0.74	0.05	1.00	0.71		0.78	0.01
PINE4	0.15	0.17	0.21	0.32	0.23	0.46	0.72	0.07	0.40	0.46	0.01	0.09	0.02	0.80	0.28	0.44	0.07		0.33
SANB3	0	0.73	0.29	0.27	0.02	0.19	0.48	0.08	0.42	0.77	0.03	0	0.17	0.01	0	0.36	0	0.08	

Panel C: Dissimilarities between banks (Upper triangle for 2019 and lower triangle for 2020)

Banks	ABCB4	BAZA3	BBAS3	BBDC3	BEES3	BGIP4	BIDI3	BMEB4	BMGB4	BNBR3	BPAC3	BPAN4	BRIV4	BRSR3	IDVL3	ITSA3	ITUB3	PINE4	SANB3
ABCB4		0.39	0.44	0.42	0.42	0.53	0.49	0.50		0.58	0.58	0.46	0.44	0.39	0.45	0.45	0.42	0.50	0.43
BAZA3	0.35		0.45	0.43	0.43	0.49	0.62	0.39		0.40	0.45	0.39	0.48	0.35	0.40	0.61	0.44	0.39	0.45
BBAS3	**0.24****	0.39		**0.23*****	0.39	0.49	0.61	0.52		0.42	0.55	0.39	0.53	0.36	0.47	**0.27****	**0.24****	0.42	0.33
BBDC3	**0.24****	0.41	**0.17*****		0.39	0.56	0.62	0.54		0.50	0.53	0.39	0.56	0.37	0.59	**0.23*****	**0.25****	0.54	0.34
BEES3	**0.24****	0.37	**0.27****	**0.22****		0.56	0.52	0.46		0.47	0.54	0.41	0.47	0.39	0.33	0.40	0.45	0.34	0.44
BGIP4	0.40	0.36	0.40	0.46	0.48		0.62	0.51		0.50	0.53	0.56	0.52	0.46	0.54	0.52	0.48	0.58	0.41
BIDI3	0.54	0.49	0.54	0.52	0.50	0.55		0.54		0.62	0.63	0.58	0.62	0.56	0.68	0.70	0.68	0.75	0.64
BMEB4	**0.25****	**0.29***	**0.30***	**0.31***	0.33	0.37	0.50			0.57	0.61	0.53	0.46	0.56	0.39	0.55	0.52	0.53	0.51
BMGB4	**0.19*****	**0.31***	**0.31***	**0.28****	**0.25****	0.33	0.42	**0.23****											
BNBR3	0.45	0.38	0.41	0.40	0.38	0.49	0.40	0.41	0.41		0.45	0.63	0.39	0.34	0.62	0.55	0.51	0.58	0.55
BPAC3	0.42	**0.31****	**0.34***	**0.32****	0.35	0.46	0.56	0.44	0.45	0.58		0.61	0.56	0.52	0.42	0.57	0.51	0.56	0.51
BPAN4	**0.31***	0.49	**0.30***	**0.26****	**0.24****	0.46	0.50	0.38	0.35	0.44	**0.35***		0.51	0.43	0.50	0.45	0.34	0.35	0.56
BRIV4	0.35	0.40	0.34	0.33	**0.31***	0.48	0.52	0.37	0.35	0.44	0.38	**0.31***		0.49	0.53	0.56	0.46	0.33	0.62
BRSR3	**0.28****	0.40	**0.27****	**0.23*****	**0.25****	0.42	0.58	0.34	**0.29***	0.48	0.39	**0.26****	0.35		0.38	0.44	0.45	0.44	0.43
IDVL3	0.39	0.31	0.42	0.40	0.42	0.32	0.48	0.40	0.37	0.54	0.48	0.40	0.45	0.39		0.61	0.53	**0.27****	0.67
ITSA3	**0.27****	0.33	**0.23*****	**0.20*****	**0.24****	0.49	0.50	**0.24****	**0.28****	0.34	0.37	**0.26****	0.36	**0.24****	0.43		**0.30***	0.61	0.35
ITUB3	0.29*	0.41	**0.22****	**0.18*****	**0.29***	0.48	0.50	0.37	0.35	0.41	0.37	**0.30***	0.31	**0.30***	0.44	**0.23*****		0.51	**0.31***
PINE4	**0.25****	**0.34***	**0.28****	**0.26****	**0.24*****	0.50	0.43	**0.31***	**0.25****	0.38	0.44	**0.27****	0.34	**0.28****	0.44	**0.22*****	0.35		0.52
SANB3	0.32	0.42	**0.24****	**0.21*****	**0.22****	0.47	0.54	0.39	0.34	0.41	0.37	**0.26****	0.33	**0.29****	0.43	**0.25****	**0.22*****	0.34	

Notes: [a] The Granger causalities and dissimilarities were calculated considering the periods may to December, 2019, and January to august, 2020. [b] Considering the 2019 period, BMGB4 did not have a robust return series (more than 30 consecutive days), thus for some of the analysis there are no tabulated values. [c] The p-values are derived from Monte Carlo simulations with 5.000 runs tanking red noise as null hypothesis: * stands for $p < 10\%$, ** for $p < 5\%$ and *** for $p < 1\%$. [d] For Granger causalities tests, the unconditional VAR was used for the combinations index versus bank while for the combinations bank versus bank the conditional VAR was implemented, tanking Ibovespa and IFNC as control variables, both lagged. [e] The blue and red colour stand, respectively, for unidirectional and bidirectional Granger causality.

Figure 5: Wavelet Coherence vs Partial Wavelet Coherence (controlled by COVID-19) of selected bank pairs.



Notes: [a] The cone of influence is shown as the black convex curve. The 5% significance level contours are in black and are derived from Monte Carlo simulations with 5000 runs assuming red noise as null hypothesis. [b] Data from January 29 to August 31, 2020. Source: Economatica, B3 and Johns Hopkins Corona Virus Research Center.

5 CONCLUSION

In the early 2020 the world faced the beginning of a crisis never seen before. The fast escalate of cases and deaths led governments to adopt a series of measures, basically restricting the movement of people and the bulk of business, causing tremendous economic and financial impacts worldwide. Many studies arose analysing theses effects in consequence of this pandemic.

We add to the COVID-19 literature by investigating the Brazilian banking sector reaction to COVID-19 numbers, from January 29 to August 31, 2020. Precisely, we apply the wavelet framework and Granger causality tests to assess the relationship between the returns of the Brazilian financial index, IFNC, and cases or deaths due to COVID-19 in the Hubei province, China, in countries who stood out in this health crisis scenario and the world.

Our results suggest there are significant conditional co-movements relationships between the COVID-19 numbers and the financial series. We highlight the fact that most of the significant relations occurs at high frequency intervals and the cases in Brazil and US and deaths in France series are the first to lead intuitively in an anti-phasic way the IFNC index by the most difficult moment of the pandemic, in late March 2020. Besides, we also identify some cases in which the financial index is leading in anti-phase movement. This situation can be interpreted as the Brazilian stock market foreseeing a possible increase or decrease in the number of cases.

We also take a closer look inside the banking sector, by analysing the co-movements between the bank stocks returns during the pandemic. After imposing some restrictions, we find ITSA3 and BPAN4 play key roles in the pass-through path for the banking sector. Moreover, the former experienced soft drops in its prices, confirming one of Ding *et al*. (2020) conclusions. We also find an increase in the links between the banking stocks, by comparing the Granger causalities and Dissimilarities relationships before and after the pandemic. Finally, adopting Wu *et al*. (2020) procedure, we verify there is a reduction in significant coherency areas between the bank returns once the COVID-19 presence is removed in most bank pairs considered, what reinforces it effects on the banking sector.

Overall, it is clear COVID-19 relevance to the Brazilian banking sector co-movements, either affecting its financial index or the bank linkages. These results provides a good look on the sector behavior and offers some useful insights to investors and portfolio managers as decision makers agents in this chaotic scenario.

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APPENDIX
Table A1. Bank List, Ticker Symbols and Market Values.

Bank	Ticker Symbol	Market Value (US$M) in December 2020
Banco ABC Brasil	ABCB4	331.98
Banco Amazonia	BAZA3	240.74
Banco do Brasil	BBAS3	21,394.00
Banco Bradesco	BBDC3	43,815.95
Banco do Estado do Espírito Santo	BEES3	340.75
Banco do Estado do Sergipe	BGIP4	103.65
Banco Inter	BIDI3	4,847.03
Banco Mercantil do Brasil	BMEB4	165.47
Banco BMG	BMGB4	229.54
Banco do Nordeste	BNBR3	1,263.15
BTG Pactual	BPAC3	18,116.57
Banco PAN	BPAN4	1,004.03
Banco Alfa de Investimento	BRIV4	152.75
Banrisul	BRSR3	1,194.60
Voiter	IDVL3	N.A.
Itaúsa	ITSA3	19,324.12
Itaú Unibanco	ITUB3	56,143.15
Banco Pine	PINE4	71.85
Banco Santander Brasil	SANB3	32,549.94

Source: B3.