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ANTÔNIO CRISTIANO DE OLIVEIRA COSTA

ESSAYS ON THE INTERNATIONAL FINANCIAL MARKETS IMPACTS OF COVID-19

FORTALEZA
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Orientador: Prof. Dr. Paulo Rogério Faustino de Matos.
Coorientador: Prof. Dr. Cristiano da Costa da Silva.

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Aprovada em: ___/___/______.

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A Deus.

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RESUMO

Essa tese é composta de cinco artigos tratando dos efeitos da pandemia de COVID-19 sobre os mercados financeiros internacionais. O primeiro artigo é entitulado “COVID-19, stock market and sectoral contagion in the US: A time-frequency analysis”. Ele primeiro investiga as relações condicionais entre o S&P 500 e os números da COVID-19 nos países mais afetados, Hubei e mundo, usando o arcabouço de wavelet parcial. Ele mostra que os ciclos de curto prazo de mortes na Itália nos primeiros dias de março lideraram o S&P 500 fora de fase. Além disso, que os ciclos de baixa frequência do S&P 500 no início de abril anteciparam os ciclos de mortes nos EUA. Em seguida, examina o repasse setorial por meio da causalidade de Granger e o contágio por meio de técnicas de tempo-frequência, ressaltando o papel estratégico do setor de energia, a previsibilidade dos ciclos de Telecom e a presença de contágio. O segundo artigo intitula-se “On the relationship between COVID-19 and Brazilian financial market” e desenvolve uma análise semelhante à primeira aplicada ao caso brasileiro. Metodologicamente, este artigo se diferencia do primeiro ao usar um VaR baseado em wavelet para investigar o contágio setorial. Ele demonstra que as mortes nos EUA, China, Itália e Brasil e os casos nos EUA, Itália, França e Brasil foram as séries mais relevantes para o desempenho do IBOV. Entre os setores, constata-se o contágio, além disso, que Utilidades Públicas e Energia Elétrica apresentam alto poder de previsibilidade. O artigo “On the risk-based contagion of G7 banking system and the COVID-19 pandemic” investiga como o risco individual e sistêmico dos índices do setor financeiro / bancário do G7 evoluiu durante a pandemia COVID-19. Ele usa métricas tradicionais de risco e métricas de domínio de tempo-frequência. Encontra um aumento generalizado nas medidas de risco individual e sistêmico. Além disso, o aumento do poder de previsibilidade dos setores financeiros de países altamente afetados, particularmente EUA e Itália. O artigo “On the relationship between COVID-19 and G7 banking co-movements” examina o co-movimento dos índices do setor financeiro / bancário do G7 usando coerência wavelet, e a comparação entre coerência e coerência parcial ao controlar para números COVID-19 mundiais. Ele também emprega um teste estatístico de contágio. Os resultados indicam um aumento acentuado no co-movimento e que os números da COVID-19 podem explicar esse aumento de forma razoável. O contágio financeiro é confirmado pelo teste estatístico realizado em 30 dos 42 casos. O último artigo, “Sectoral connectedness: New evidence from US stock market during COVID-19 pandemics”, trata principalmente das mudanças na conexão setorial dos Estados Unidos ocorridas durante a pandemia de COVID-19 e de fatos estilizados relativos a setores específicos. Ele usa os índices de transbordamento / conexão de Diebold e Yilmaz

(2009, 2012, 2014). Ele encontra um aumento extraordinário na conexão, desde os primeiros estágios do espalhamento internacional da doença até o final de julho de 2020. Ele também mostra mudanças das conexões (níveis e direções) quando observadas aos pares de setores. Finalmente, o setor Financeiro mostrou ser o emissor relevante de spillovers em uma série de métricas.

Palavras-chave: COVID-19. Mercado financeiro. Contágio financeiro. Conectividade. Relações condicionais de liderança.

ABSTRACT

This thesis is comprised of five articles on the effects of COVID-19 pandemic over the international financial markets. The first article is titled "COVID-19, stock market and sectoral contagion in the US: A time-frequency analysis". It first investigates the conditional relationships between the S&P 500 and the COVID-19 numbers on the most affected countries, Hubei and word, using the partial wavelet framework. It finds short-term cycles of deaths in Italy in the first days of March to lead out-of-phase S&P 500. Also, low frequency cycles of S&P 500 in early April anticipate the cycles of deaths in the US. Then it examines the sectoral pass-through using granger causality, and contagion using time-frequency techniques, finding the strategic role of the energy sector, predictability of the Telecom cycles, and presence of contagion. The second article is titled "On the relationship between COVID-19 and Brazilian financial market" and develops an analysis similar to the first applied to the Brazilian case. Methodologically this article differentiates from the first by using a wavelet based VaR to investigate the sectoral contagion. It finds deaths in US, China, Italy, and Brazil and cases in US, Italy, France, and Brazil to be the most relevant to IBOV performance. Among sectors, contagion has been evidenced, furthermore, Public Utilities and Electrical Energy are shown to have high predictability power. The article "On the risk-based contagion of G7 banking system and the COVID-19 pandemic" investigates how individual and systemic risk of G7 financial/banking sector indices evolved during the COVID-19 pandemic. It uses traditional metrics of risk and time-frequency domain metrics. It finds a widespread increase in individual and systemic risk measures. Also, the increase of predictability power of financial sectors from highly affected countries, particularly US and Italy. The article "On the relationship between COVID-19 and G7 banking co-movements" looks to the co-movement of G7 financial/banking sector indices using wavelet coherence, and the comparison between coherence and partial coherence when controlling for world COVID-19 numbers. It also employs a statistical test of contagion. The findings indicate a sharp increase in the co-movement and that the word COVID-19 numbers can explain this increase fairly. The contagion effect is confirmed by the statistical test performed in 30 out of 42 cases. The last article, "Sectoral connectedness: New evidence from US stock market during COVID-19 pandemics", is mainly concerned with the changes in the US sectoral connectedness occurred during the COVID-19 pandemic and stylized facts regarding specific sectors. It uses the spillovers/connectedness indices of Diebold and Yilmaz (2009, 2012, 2014). It finds an extraordinary increase in connectedness lasting from first stages of international spread to the end of July 2020. It also shows pairwise (levels and directions) changes in connectedness. Finally, Financials has been shown to be relevant sender of spillover in a number of metrics.

Keywords: COVID-19. Financial markets. Financial contagion. Connectedness. Lead-lag conditional relationships.

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LIST OF ABREVIATIONS AND ACRONYMS

COVID-19	Coronavirus disease 2019
G7	Group of Seven
GARCH	Generalized Autoregressive Conditional Heteroskedasticity
GFC	Global Financial Crisis
GICS	Global Industry Classification Standard
IBOV	Ibovespa, Brazilian main stock index
S&P	Standard and Poor’s
VaR	Value at Risk
VAR	Vector autoregression
WHO	Word Health Organization

CONTENTS

1 INTRODUCTION

The COVID-19 pandemic has been a catastrophic event for mankind, with millions of deaths spread over virtually all geographic localities in a more or less dramatic form[1]. Its impacts to the economies have been of multiple nature, stemming from loss of job productivity, fiscal pressure - given the increased cost of public funded health systems and government direct transfers -, reduced economic activity due to social distancing, among many others, as discussed in Goodell (2020).

The financial market impacts have been nothing short of unprecedented. Indeed, by many metrics COVID-19 has been the most devastating[2] contagious disease in terms of impacts to the financial markets, even considering the Spanish Flu.

Given this backdrop, the COVID-19 provides rare research opportunity to investigate how the financial market dynamics evolve under extreme conditions. More specifically, it provides opportunities to better understand how the numbers of cases and deaths relate to the financial markets during a health crisis; to investigate the presence of financial contagion among different sectors in a specific economy or between strategic sectors of different economies; to understand how connected sectors can be during extraordinary moments; to check which are the most critical economic sectors in terms of sending and receiving spillovers and so on. The present thesis pursues the research problems above stated.

The main body of this thesis is comprised of five articles/chapters and focuses on the effects of COVID-19 pandemic over the international financial markets. The first article studies how COVID-19 numbers and the US market performance are related, and how its sectoral co-movement evolved. The second article repeats the first exercise for the Brazilian scenario using a slightly different approach to contagion measurement. The third and the fourth articles are dedicated to aspects of G7 banking sector risk and co-movement during the pandemic. The last article studies the sectoral connectedness in the US.

All the articles are joint work with Paulo Matos and Cristiano da Silva. As of the writing of this introduction, the first, third and last articles had been peer reviewed and accepted for publication on Research in International Business and Finance, Global Business Review and Finance Research Letters, respectively. The second and fourth articles are going through the peer review process.

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[1] As of June 06, 2021, there are 173 million cases, with more than 3.7 million deaths recorded in 222 countries, according to the WHO, available at https://covid19.who.int/, last accessed on June 07, 2021.

[2] See Baker et al. (2020) for an analysis applied to the US case going back to 1900.

The first article is titled “COVID-19, stock market and sectoral contagion in the US: A time-frequency analysis”. It first develops an investigation on the conditional relationships between the US stock index and the number of cases and deaths observed on the most affected countries, Hubei and word, using the partial wavelet framework as the methodology and the Fama and French (2015) five factors as controls. Then it examines the sectoral pass-through using granger causality, and contagion using time-frequency techniques based on Aguiar-Conraria and Soares (2011) and Wu et al. (2020).

The second article is titled “On the relationship between COVID-19 and Brazilian financial market” and develops an analysis similar to the first article applied to the Brazilian market case. Methodologically this article differentiates from the first by using a wavelet based VaR to investigate the sectoral contagion, following Rua and Nunes (2009).

The third article is titled “On the risk-based contagion of G7 banking system and the COVID-19 pandemic”. It investigates how the individual and systemic risk of financial/banking sector indices from the G7 have evolved during the COVID-19 pandemic. It uses both traditional metrics of risk, as drawdown and volatility, and the time-frequency domain metrics of dissimilarities and wavelet based VaR.

The fourth article is titled “On the relationship between COVID-19 and G7 banking co-movements”. It looks to the co-movement of G7 financial/banking sectors indices using wavelet coherence, then the comparison between wavelet coherence and partial wavelet coherence when controlling by world COVID-19 deaths and cases. Finally, it employs a statistical test of contagion developed by Forbes and Rigobon (2002) and further discussed in Fry et al. (2010).

The last article is titled “Sectoral connectedness: New evidence from US stock market during COVID-19 pandemics”. It is mainly concerned with the changes in the US sectoral stock indices connectedness occurred during the COVID-19 pandemic and stylized facts regarding specific sectors that may have arisen. It uses the mainstream methodology developed by Diebold and Yilmaz [3](2009, 2012, 2014), through which static and dynamic analysis of spillovers/connectedness indices and tables are performed.

There is a thematic common ground to all the articles, but they are not dependent on one another. Also, we have opted to add a subsection with the references in each chapter to make them more self-contained. Thus, we understand the reader does not need to follow any particular order on reading this thesis to obtain a better understanding.

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[3] There are myriads of network approaches to economics and finance. For an excellent overview of many useful techniques that are not specifically covered in this thesis, refer to Jackson (2008).

2 COVID-19, STOCK MARKET AND SECTORAL CONTAGION IN THE US: A TIME-FREQUENCY ANALYSIS

2.1 Introduction

The novel coronavirus outbreak, which began in Wuhan, China, in December 2019, has expanded to touch every corner of the world, and on March 11, 2020, the World Health Organization defined it to be of a global nature. A pandemic scenario is neither new nor rare, so that there are similarities between the current moment and other ones of humanity, in which diseases spread throughout the globe and caused havoc.

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

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

As serious as the numbers are the impacts. The hesitation and contradiction in the measures adopted by policy makers in most countries severely affected by the virus, and the specific issues of this pandemic – insufficient hospital capacity, social distancing, a possible second wave and the uncertainty caused in the productive sectors –made its impact on the economy quickly devastating. The long-term consequences are difficult to predict.

An interesting starting point in this discussion is Goodell (2020). According to this objective survey, some of the main concerns with this pandemic arise from rising costs for health systems, loss of job productivity, social distance that disrupts economic activity, depressed tourism and impacts on foreign direct investment. In this context, Welfens (2020) highlights that a broader and deeper analytical link between health system analysis and macroeconomic approaches seems to be adequate.

Regarding the macroeconomic sectors, they tend to suffer strong and asymmetric impacts in every crisis. Studies such as Kaplan et al. (2020) that measure the effect of the fall in housing net worth on household expenditures during the Great Recession, or Aloui et al.

(2020), that propose assessing the impact of COVID-19 shocks on the energy futures markets on crude oil and natural gas, can be useful to predict the impacts of the current crisis on macroeconomic environment.

Moreover, still regarding the literature on the impacts of this pandemic, some of them are not on the real side of the economy. In Conlon, Corbet and McGee (2020), one can see the impacts on cryptocurrency markets, while according to Leslie and Wilson (2020), due to the increase in family isolation, unemployment, and economic stress, the pandemic increased domestic violence calls by 7.5% from March to May 2020.

Concerning specifically the financial impacts, Goodell (2020) addresses the stock market evidence based on a literature that have either prognosticated such a chaotic large-scale event. Zhang, Hu and Ji (2020) highlight the change of pattern in the global stock market spillovers after the COVID-19 outbreak, corroborating Baker et al. (2020), who argue that no previous infectious disease outbreak, including the Spanish Flu, has impacted the stock market as forcefully as the COVID-19 pandemic.

There is also a very interesting empirical exercise provided by Lyócsa et al. (2020). They find that during this pandemic period, fear of the coronavirus, manifested as excess Google search volume activity, represents a timely and valuable data source for forecasting stock price variation around the world.

In this debate on the financial effects of COVID-19, we highlight Ashraf (2020). This paper proposes using daily COVID-19 confirmed cases and deaths and stock market returns data from 64 countries over the period January 22, 2020, to April 17, 2020. We add to this specific discussion by proposing to measure the impact of COVID-19 on the US stock market. We are the first, to our knowledge, to assess the conditional relationship in the time-frequency domain between the cases or deaths by COVID-19 in Hubei, China, in countries with record deaths and in the world and the return on S&P 500. In a turbulent semester in the US for political reasons or for oil fluctuations and given the financial contagion through financial and nonfinancial firms during this pandemic reported in Akhtaruzzaman et al. (2021), we also analyze role of COVID-19 in the US sectoral transmission. In terms of sample size, the main limitation for the time-series span used here is due to the reality of the pandemic: it is still very recent. We use the largest possible set of variables, covering the period from January 29 to June 30, 2020, at a daily frequency. The data sources are Investing.com and Johns Hopkins Corona Virus Research Center.

Since our purpose is to study when and at what frequencies each COVID-19 variable is synchronized or not with S&P 500, besides the co-movements between sector indices in the US, we follow methodologically Aguiar-Conraria et al. (2018), by using partial wavelet coherencies, partial phase-difference diagrams, and partial gains. In both exercises, we control for a specific set of instruments, lagged Fama and French (2015) 5 factors. This mathematical framework enables us to infer on which financial cycle has been leading or lagging each disease cycle. Based on the wavelet transforms, we can also explore sectoral contagion, based on dissimilarities, Granger causality and coherencies between S&P sector indices. Our findings are useful to tell the history of the pass-through of this recent health crises across the sectors of the US economy.

The layout of the paper is the following. Section 2.2 provides a literature review. Section 2.3 outlines the methodology. Section 2.4 describes the data and presents the results. Section 2.5 offers some concluding remarks.

2.2 Recent Literature Review on Applied Wavelet Analysis

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

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

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

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

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

2.3 Methodology

2.3.1 Unconditional wavelet framework

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

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

$$dist(W_x, W_y) = \frac{\sum_{k=1}^{K} w_k^2 [d(\mathrm{l}_x^k, \mathrm{l}_y^k) + d(\mathbf{u}_k, \mathbf{v}_k)]}{\sum_{k=1}^{K} w_k^2} \tag{2.1}$$

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

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

$$W_{xy}(\tau,s) = W_x(\tau,s)\overline{W_y}(\tau,s) \tag{2.2}$$

and

$$R_{xy}(\tau,s) = \frac{|S(W_{xy}(\tau,s))|}{\sqrt{S(|W_{xx}(\tau,s)|)S(|W_{yy}(\tau,s)|)}}, \tag{2.3}$$

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

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

$$\phi_{xy}(s,\tau) = tan^{-1}\left(\frac{\Im\left(W_{xy}(s,\tau)\right)}{\Re\left(W_{xy}(s,\tau)\right)}\right), \tag{2.4}$$

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

2.3.2 Conditional wavelet framework: partial coherency, phase difference and gain

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

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

$$R_{y(x\boldsymbol{z})} = \sqrt{\frac{R_{yx}^2 + R_{y\boldsymbol{z}}^2 - 2\Re(\xi_{yx}\xi_{x\boldsymbol{z}}\overline{\xi_{y\boldsymbol{z}}})}{1 - R_{x\boldsymbol{z}}^2}} \tag{2.5}$$

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

$$\xi_{yx,\boldsymbol{z}} = \frac{\xi_{yx} - \xi_{y\boldsymbol{z}}\overline{\xi_{x\boldsymbol{z}}}}{\sqrt{(1 - R_{y\boldsymbol{z}}^2)(1 - R_{x\boldsymbol{z}}^2)}} \tag{2.6}$$

The absolute value and the angle of $\xi_{yx,\boldsymbol{z}}$ are respectively the partial wavelet coherency and the partial wavelet phase difference between y and x, after controlling for $\boldsymbol{z}$. They are analog of the bivariate metrics given by (2.3) and (2.4), and they are denoted by $R_{yx,\boldsymbol{z}}$ and $\phi_{yx,\boldsymbol{z}}$. Regarding the signs, a phase-difference of zero indicates that the time-series move together at the specified frequency. If $\phi_{yx,z} \epsilon \left(0, \frac{\pi}{2}\right)$ the series move in phase, but the time-series y leads x, while if $\phi_{yx,z} \epsilon \left(-\frac{\pi}{2}, 0\right)$ then it is x that is leading. A phase-difference of $\phi_{yx,z} = \pm\pi$ indicates an anti-phase relation. Finally, if $\phi_{yx,z} \epsilon \left(\frac{\pi}{2}, \pi\right)$, then x is leading and time-series y is leading if $\phi_{yx,z} \epsilon \left(-\pi, -\frac{\pi}{2}\right)$. We also follow Aguiar-Conraria et al. (2018), by using their general concept of wavelet gain (regression coefficient) by defining the partial wavelet gain, which can be interpreted as a regression coefficient in the regression of y on x, after controlling for $\boldsymbol{z}$, given by

$$G_{yx,\boldsymbol{z}} = \frac{|\xi_{yx} - \xi_{yz}\overline{\xi_{xz}}|}{(1 - R_{xz}^2)} \frac{\sigma_y}{\sigma_x} \tag{2.7}$$

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

2.3.3 Instruments

In our main empirical exercises based on a conditional analysis, we control for a set of specific financial variables as instruments, carefully chosen according to their forecasting potential and explanatory power in the cross-sectional dimension. We propose using the lagged Fama and French (2015) 5 factors (FF5F).

These risk factors are derived in well studied asset pricing models being returns of diversified portfolios that provide different combinations of exposures to unknown state variables. According to French Research Data Library, in addition to the excess return on the market, other factors are constructed using the 6 value-weight portfolios formed on size and book-to-market, the 6 value-weight portfolios formed on size and operating profitability, and the 6 value-weight portfolios formed on size and investment.

2.4 Data and empirical results

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

Health data set is comprised by series of deaths and cases of COVID-19 in the most affected countries until June 30, 2020: US, Brazil, United Kingdom, Italy, and France. We also use data from China and Hubei Province to analyze early stages. Based on Ding et al. (2020), we use daily log growth of 7-days moving average of new cases and deaths as our final explanatory variables.[4] This transformation account for weekends, holidays, week seasonality and outliers in the data. The data source is the Center for Systems Science and Engineering (CSSE) at Johns Hopkins University (JHU). For more details, see Dong, Du, and Gardner (2020).

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

Figure 2.1.a suggests a pattern of convergence, even in an atypical period, characterized by market turbulence. We highlight that only the consumer discretionary and the information technology sectors had cumulative gains in the period. The biggest drawdown recorded was in the energy sector. The cases for covid-19 in the selected locations (Figure 2.1.b) seem to have reached the plateau, while deaths worldwide and in the US still show increasing moving averages at the end of June 2020 (Figure 2.1.c). Summary statistics of such COVID-19 variables, such as lethality and mortality are reported in Table 2.1 (Panel C).

In the Table 2.1 (Panel A), we highlight, based on Morlet dissimilarities, the synchronization between return on S&P 500 and deaths in Italy, significant at 5%, and deaths and cases in US, significant at 10%.

Also, in the Table 2.1 (Panel B), we report the results of the Granger causality test in quantiles.

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

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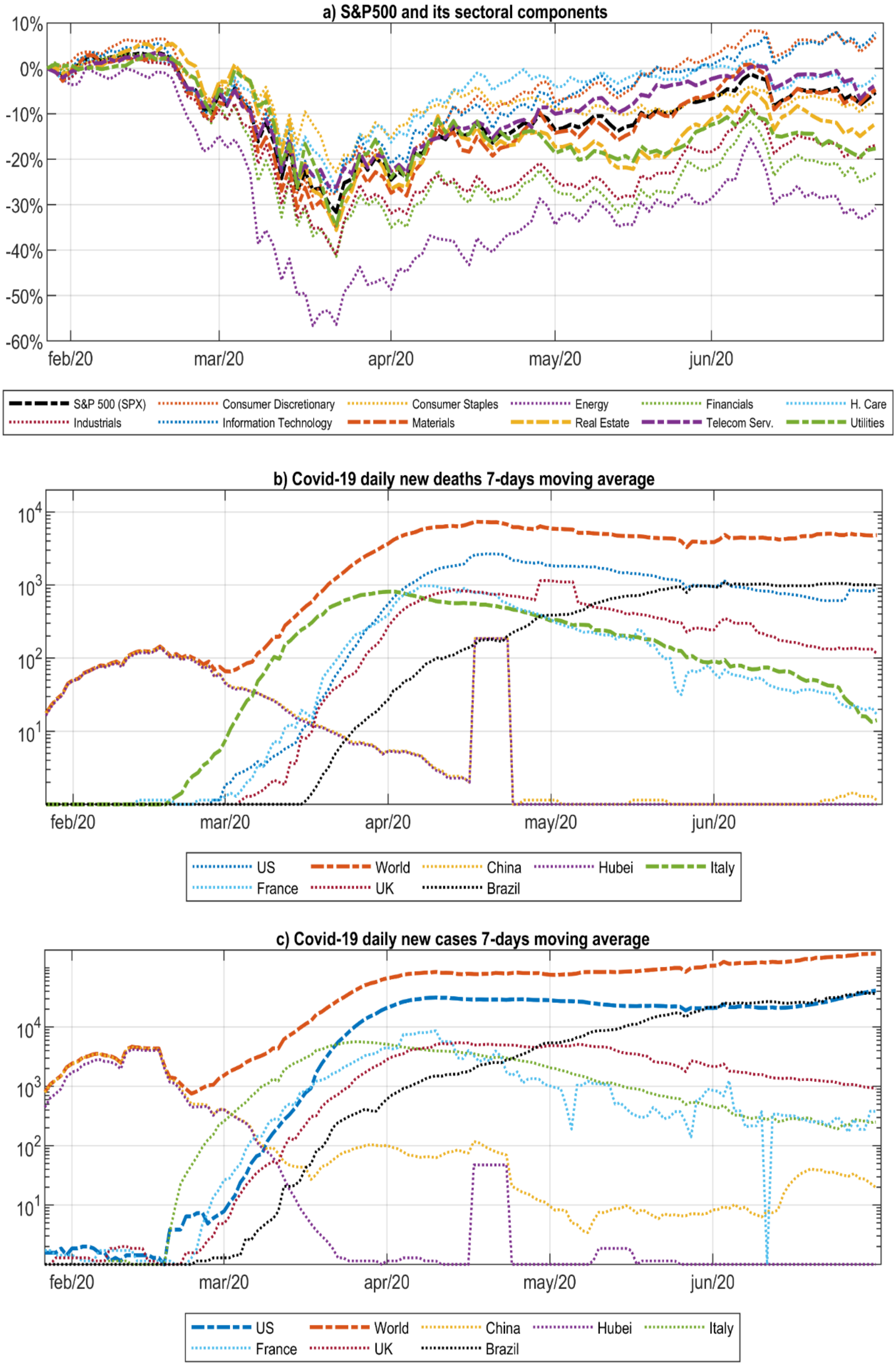
[4] We define log growth, r_t, of 7-days moving average of x_t on t as follows: $r_t = ln\big(1 + MA7(x_t)\big) - ln\big(1 + MA7(x_{t-1})\big)$, where $MA7(x_t)$ stands for the moving average of x_t on t.

Figure 2.1 – Cumulative return on S&P 500 and S&P sector indices, and COVID-19 numbers worldwide.



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

Table 2.1– US stock market and COVID-19 numbers worldwide

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

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

Based on these finding in terms of synchronization and forecasting, we perform our first exercise, aiming to see how COVID-19 deaths and cases in different localities are related to returns on S&P 500 one day ahead. We report the results for the most relevant series on Figure 2.2. The partial wavelet coherencies are plotted as 2-dimensional heat-maps. The colors range from blue (small coherency) to red (high coherency) and the cone of influence is shown with a black line. In the partial phase-difference and gain diagrams, we display mean values corresponding to three frequency intervals: 2∼4 days (short cycles), 4∼8 days (medium-term fluctuations) and 8∼16 days (long-run relationships). Considering all 16 possibilities involving S&P 500 and cases or deaths in each of the chosen locations, we plot only the figures and the diagrams with a higher incidence of regions with strong partial coherency.

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

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

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

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

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

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

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

In our second exercise, we propose evaluating the sectoral contagion between S&P sector indices during the pandemic spread. In the first step we test Granger causality based on VAR among the sector indices, conditional to the lagged FF5F. According to the results reported in Table 2.2 (Panel C), based on S&P sector indices, the first sector to react to the pandemic is the energy sector, which Granger causes the market index, and this one Granger causes the sectors of telecom and utilities.

We are also able to find sectoral contagions. Energy sector cycles are useful to predict health care cycles. Industrial sector is able to predict the financial sector, which seems to be able to forecast the cycles of the telecom and utilities sectors. Telecom cycles are also predicted by the cycles of materials and real estate sectors. It is worth mention that the sector indices that triggered out financial contagion were the most affected during this period – based on risk metrics –, indicating the importance of the COVID-19 spread in those causal relations. According to the dissimilarities in Table 2.2 (Panel D), the co-movements among the US sector indices have been stronger during COVID-19 pandemic as compared to the end of 2019. We find that the average distance between the sector indices is 0.31 at 2020, 4.7 points less than in 2019 (0.357).

Finally, we also propose better understanding the role of the COVID-19 not only in the stock market but also in the causal relations among the sectors. Aiming to complement our contagion analysis, we use the partial coherence with two different sets of controls for each of the six pair of sectors with significant Granger causality. First, we use lagged FF5F as controls, and then we use FF5F in addition to COVID-19 series (deaths in Italy and cases in US). We report the results in Figure 2.3. We find that materials vs telecom, real estate vs telecom and financials vs utilities have considerably less (from 11.2% to 18%) significant area on the second configuration partial coherence. This result suggests that the COVID-19 have been reinforcing the co-movement of those pairs of sectors. To financials vs telecom, we find a growth of 15.6% on the significant area on second configuration. This suggests that COVID-19 has contributed to weaken the co-movement of this pair of sectors. For the two remaining pairs of sectors the change was also positive but weaker (3 – 4.5%).

Figure 2.2 – Partial wavelet framework of S&P 500 vs COVID-19 controlled by lagged Fama and French (2015) 5 factors.

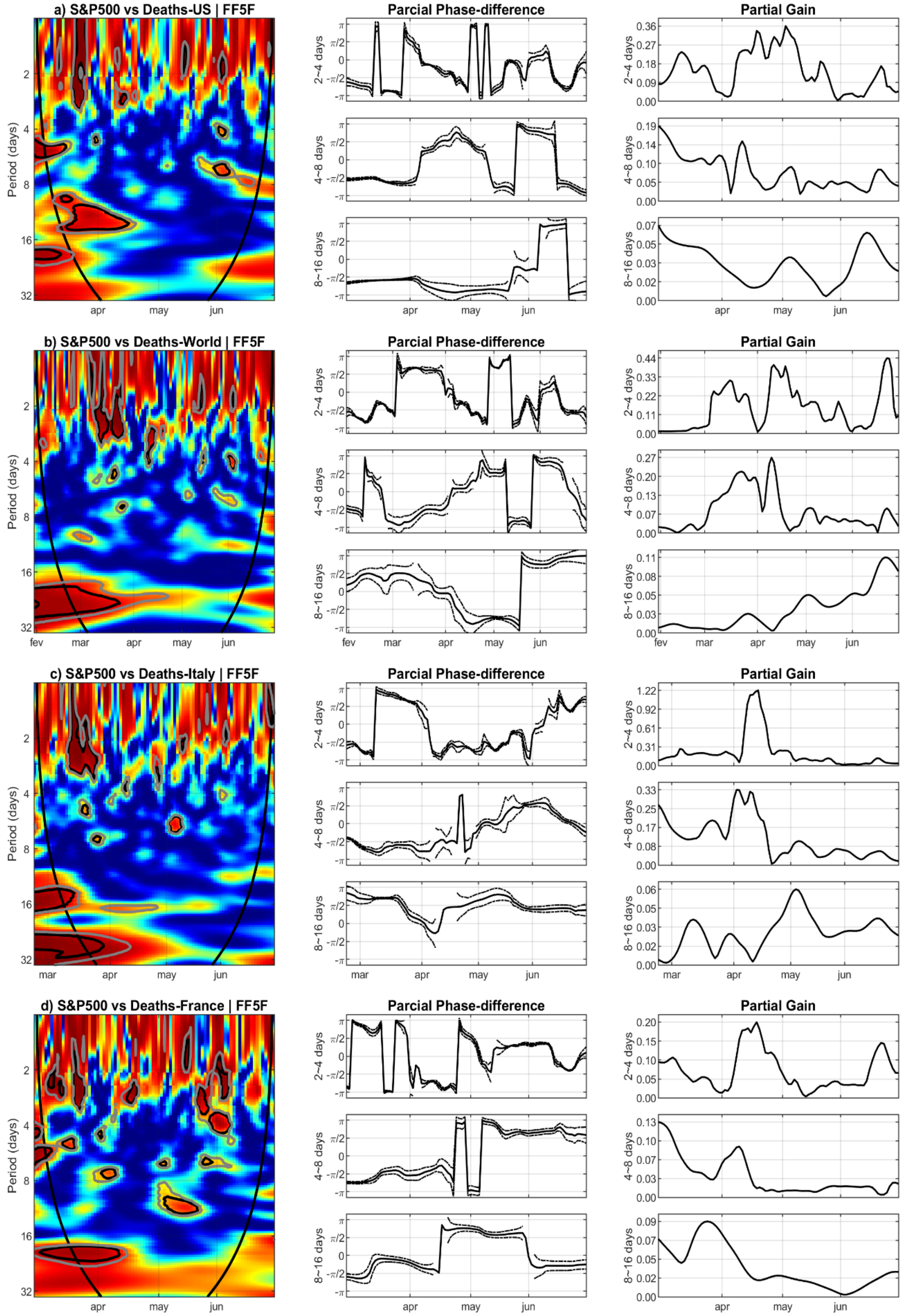


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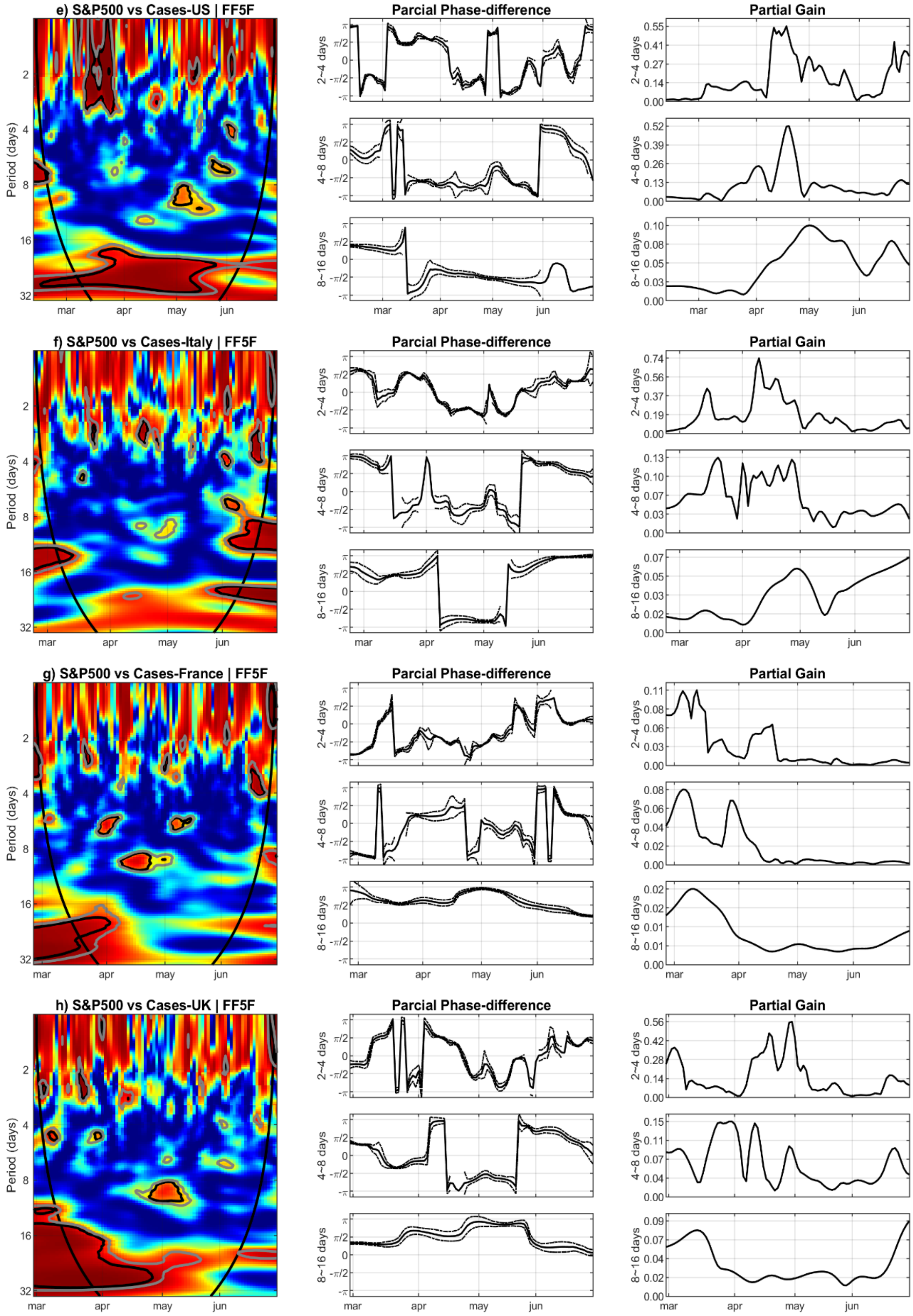
Figure 2.2 – Partial wavelet framework of S&P 500 vs COVID-19 controlled by lagged Fama and French (2015) 5 factors.



Notes: The cone of influence is shown as the black convex curve. The 5% significance level contours are in black, the 10% in gray and both are derived from Monte Carlo Simulations with 5000 runs assuming red noise as a null hypothesis. Data from January 29 to June 30, 2020. Source: Investing.com and Johns Hopkins Corona Virus Research Center.

Table 2.2 – Summary statistics, dissimilarities and Granger causality of S&P 500 and its sector indices.

Panel A: Summary statistics of US sector indices

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

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

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

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

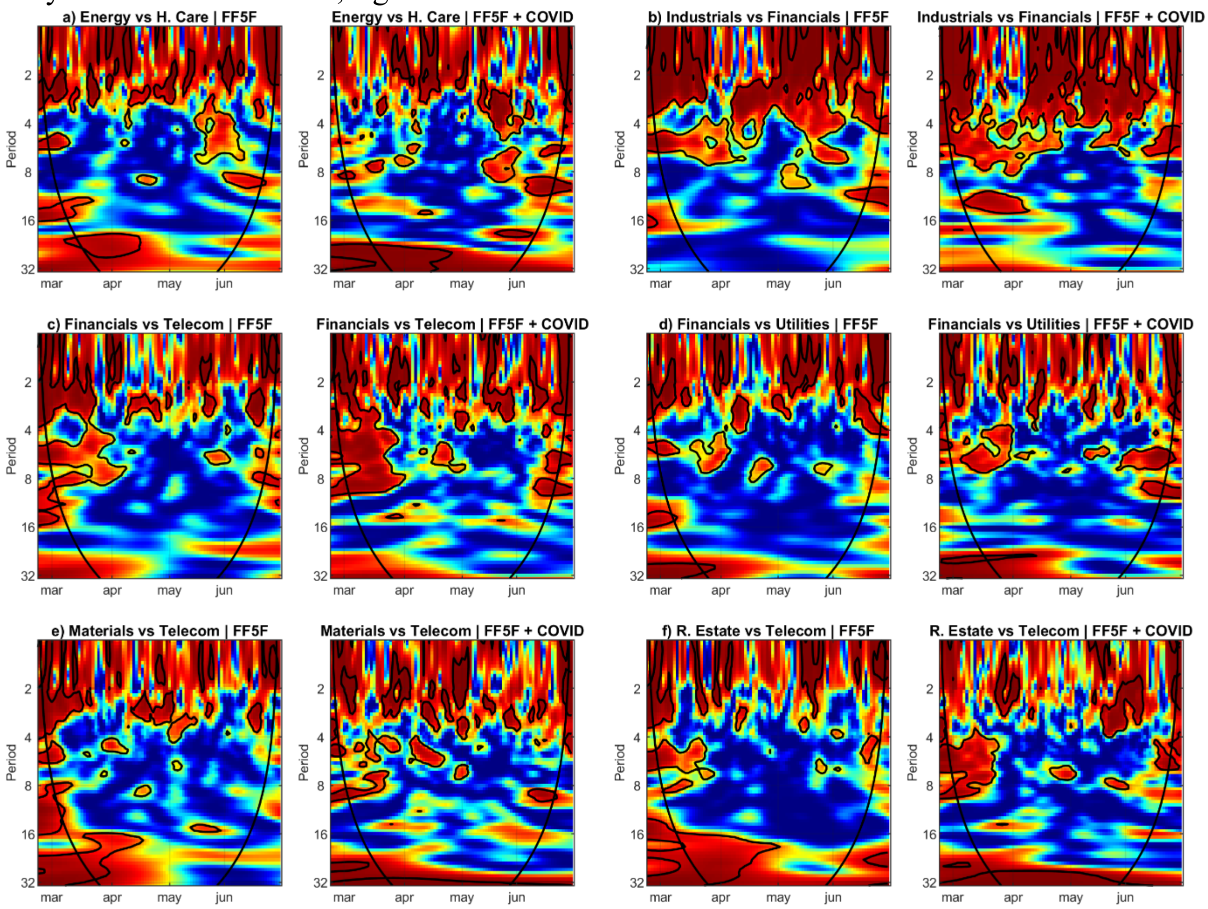
Indices	SPLRCD	SPLRCS	SPNY	SPSY	SPXHC	SPLRCI	SPLRCT	SPLRCM	SPLRCREC	SPLRCL	SPLRCU
S&P 500 Consumer Discretionary (SPLRCD)	-	0.2	0.29	0.42	0.38	0.16	0.91	0.24	0.9	0.93	0.96
S&P 500 Consumer Staples (SPLRCS)	0.61	-	0.8	0.51	0.13	0.45	0.13	0.25	0.93	0.32	0.43
S&P 500 Energy (SPNY)	0.54	0.82	-	0.62	**0.02**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

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

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

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

Figure 2.3 – Partial wavelet of selected pair of sector indices controlled by lagged Fama and French (2015) 5 factors (FF5F), left, and lagged FF5F and COVID-19 series represented by Italy deaths and US Cases, right.



Notes: The cone of influence is shown as the black convex curve. The 10% significance level contours are also in black and are derived from Monte Carlo Simulations with 5000 runs assuming red noise as a null hypothesis. Data from February 23 to June 30, 2020. Source: Investing.com and Johns Hopkins Corona Virus Research Center.

2.5 Conclusion

We revisit the debate promoted by Ashraf (2020), by assessing the conditional relationship in the time-frequency domain between the cases or deaths by COVID-19 in Hubei, China, in countries with record deaths and in the world and the return on S&P 500, for the period from January 29 to June 30, 2020.

We believe having offered useful findings to the financial market, such as the significant predictive power of deaths in Hubei and China based on the quantile Granger causality (left tail of the conditional distribution), for instance, or the evidence that short-term cycles of deaths in Italy in the first days of March and soon afterwards, cycles of deaths in the world are able to lead out-of-phase cycles of the US stock market index. We invite researchers and policy makers to use the information that the low frequency cycles of the US market index in the first half of April are useful to anticipate in an anti-phasic way the cycles of deaths in the US.

We can compare some of our findings with previous findings for 64 countries reported in Ashraf (2020). According to him, negative market reaction was strong during early days of confirmed cases and then between 40 and 60 days after the initial confirmed cases and these markets reacted more proactively to the growth in number of confirmed cases than deaths.

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

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

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

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3 ON THE RELATIONSHIP BETWEEN COVID-19 AND BRAZILIAN FINANCIAL MARKET

3.1 Introduction

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

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

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

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

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

Sharif, Aloui and Yarovaya (2020) use the coherence wavelet method and the wavelet-based Granger causality tests applied to US stock market. They find that COVID-19 risk is perceived differently over the short and the long-run and may be firstly viewed as an economic crisis, for the period from January 21 to March 30, 2020.

More recently, Matos, Costa, and da Silva (2020) propose assessing the conditional relationship in the time-frequency domain between the return on S&P 500 and the cases or deaths by COVID-19 in Hubei, China, countries with record deaths and the world, for the period from January 29 to June 30, 2020. They find that short-term cycles of deaths in Italy in the first days of March and soon afterwards, cycles of deaths in the world are able to lead out-of-phase US stock market. They also report that find that low frequency cycles of the US market index in the first half of April are useful to anticipate in an anti-phasic way the cycles of deaths in the US. Concerning the sectoral contagion, they find that the energy sector seems to be the first to react to the pandemic, and that the predictability of the Telecom cycles are useful to tell the history of the pass-through of this recent health crises across the sectors of the US economy.

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

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

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

The layout of the remaining of this paper is the following: Section 3.2 outlines the methodology, while Section 3.3 describes the data and presents the results. Section 3.4 offers some concluding remarks.

3.2 Methodology

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 Zang (1996 and 1997) and Ramsey and Lampart (1998), and in finance, as in Rua and Nunes (2009), and Reboredo and Rivera-Castro (2014). This method is well suited to our intent, since it enables us to trace transitional changes across time and frequencies, improving the analysis of cycles on the comparison to the traditional methods. We follow most of the recent empirical contributions, as Matos et al. (2020) by using Morlet as the continuous complex-valued mother wavelet. This function is ideal for the analysis of oscillatory signals since it provides an estimate of the instantaneous amplitude and instantaneous phase of the signal in the vicinity of each time/frequency location (τ, s).

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

$$dist(W_x, W_y) = \frac{\sum_{k=1}^{K} w_k^2 [d(\mathrm{l}_x^k, \mathrm{l}_y^k) + d(\mathbf{u}_k, \mathbf{v}_k)]}{\sum_{k=1}^{K} w_k^2} \tag{3.1}$$

The wavelet transforms of x and y are given by $W_x(.)$ and $W_y(.)$, respectively. Moreover, w_k^2 are the weights equal to the squared covariance explained by each axis, $\mathbf{u}_k$ and $\mathbf{v}_k$ are singular vectors satisfying variational properties and l_x^k and l_y^k are leading patterns. K is the number of singular vectors used to capture the covariance in the data. In this work we used

K=3 for all computations of dissimilarities. The full description of the dissimilarity measure used is provided by Aguiar-Conraria and Soares (2011).

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

$$W_{xy}(\tau, s) = W_x(\tau, s)\overline{W_y}(\tau, s) \quad (3.2)$$

and

$$R_{xy}(\tau, s) = \frac{|S(W_{xy}(\tau,s))|}{\sqrt{S(|W_{xx}(\tau,s)|)S(|W_{yy}(\tau,s)|)}} \quad (3.3)$$

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

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

$$\phi_{xy}(s, \tau) = tan^{-1}\left(\frac{\Im\left(W_{xy}(s,\tau)\right)}{\Re\left(W_{xy}(s,\tau)\right)}\right), \quad (3.4)$$

where R(.) and I(.) are the real and the imaginary parts of the cross wavelet spectrum.

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

We follow Aguiar-Conraria et al. (2018), by using the partial wavelet framework.

Hence, the partial wavelet coherency between y (index) and x (COVID-19) after controlling for z is given by

$$\xi_{yx,\boldsymbol{z}} = \frac{\xi_{yx} - \xi_{y\boldsymbol{z}}\overline{\xi_{x\boldsymbol{z}}}}{\sqrt{(1-R_{y\boldsymbol{z}}^2)(1-R_{x\boldsymbol{z}}^2)}} \quad (3.5)$$

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

$$G_{yx,\boldsymbol{z}} = \frac{|\xi_{yx} - \xi_{y\boldsymbol{z}}\overline{\xi_{x\boldsymbol{z}}}|}{(1-R^2_{x\boldsymbol{z}})} \frac{\sigma_y}{\sigma_x} \tag{3.6}$$

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

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

3.3 Data and empirical results

3.3.1 Data

In terms of sample size, the main limitation for the time-series span is due to the pandemic duration. We use the largest possible set, covering the period from January 22 to July 31, 2020, at a daily frequency.

Health data set is comprised by series of deaths and cases of COVID-19 in the most affected countries by June 30, 2020: US, Brazil, United Kingdom, Italy, and France. We also use data from China and Hubei Province to analyze early stages. Based on Ding et al. (2020), we use daily log growth of 7-days moving average of new cases and deaths as our final explanatory variables. This transformation account for weekends, holidays, week seasonality and outliers in the data. The data source is the Center for Systems Science and Engineering (CSSE) at Johns Hopkins University (JHU). For more details, see Dong, Du, and Gardner (2020). Thus, after transformations, and considering that we used the first lag of COVID-19 variables, we start actual analysis on January 31, 2020.

Concerning the financial variables5, we use daily returns on the main broad Brazilian stock index, Ibovespa (IBOV), and on its 7 sector indices: Basic Materials (IMAT), Electrical Energy (IEE), Industrials (INDX), Consumption (ICON), Financials (IFNC), Public

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

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

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

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

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

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

Figure 3.1.a suggests a pattern of convergence during the pandemic, giving the first hint of contagion among sectors. We highlight that only the Basic Materials (IMAT) had cumulative gains in the period. The drawdowns recorded were between 34,0% (Electrical Energy - IEE) and 54.4% (Real State – IMOB).

The 7 days moving average of covid-19 deaths in the selected locations (Figure 3.1.b) seem to show that the worst is now behind for most countries. The record high world numbers have been reached in mid-April and, since that, most countries have reached plateaus or show decaying number of deaths. We highlight that Brazil took the longest among the selected locations to begin a plateau (only on beginning of June) and that the US was the only locality were some relevant degree of recrudescence of deaths was observed in July.

As for the moving average of cases (Figure 3.1.c) in the world, we have had a local maximum in the end of March and, after a little decrease, a slowly but surely increase in the numbers have been observed. Here we note that US had a very similar behavior to the world, that Brazil did not visually reached a maximum up to the end of July and that most of the other locations depicted here seem to have decreasing numbers for a while and then experienced increasing numbers by the end of June.

It is notetaking, and relevant to the present study, the fact that we have 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, is more evident for world, European countries, and China, while in Brazil and US we also can see that the number of deaths has decreased (or increased) less than the number of cases. This disparity of patterns suggests that investors may have had heterogeneous perceptions of the deaths and cases data along different moments of the pandemic, which highlight the importance of the wavelet methods used in the present paper.

Summary statistics of the COVID-19 variables, such as lethality and mortality are reported in Table 3.1 (Panel C). In the Table 3.1 (Panel A), we highlight, based on Morlet dissimilarities, the synchronization between returns on IBOV and the COVID-19 series. As can be seen there, most dissimilarities are significant at 10% (except for deaths in France and Brazil and cases in China, Hubei, and France). Both cases and deaths in US are significant at 1% as is cases in Italy. Deaths in Italy and UK, and cases in world, UK and Brazil are significant at 5%. This means that the IBOV and the COVID-19 series have similar content when compared in the time-frequency plain, suggesting, in a very preliminary stage, that the selected variables may in fact have some good information about each other.

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

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

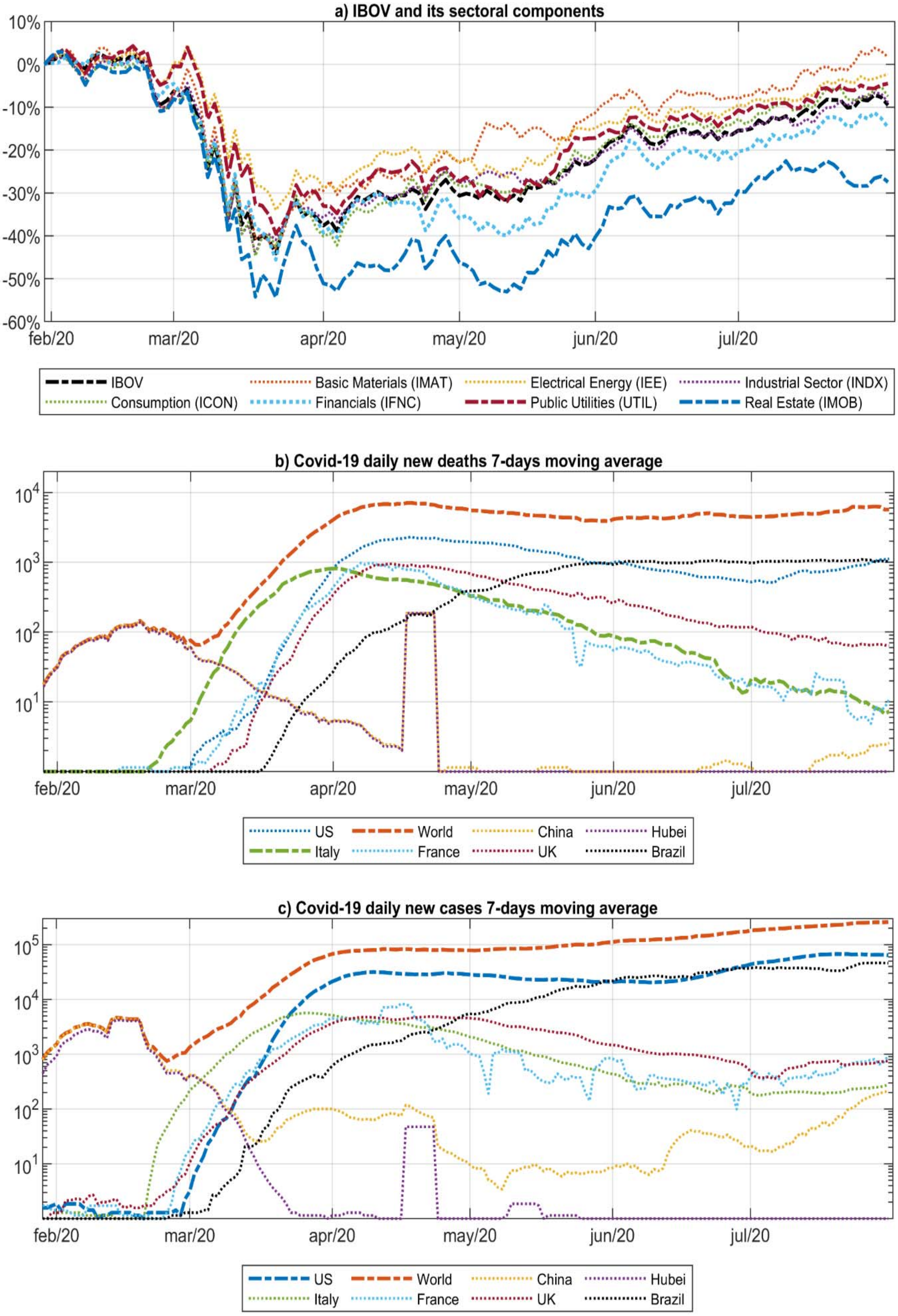
We report the results for the most relevant series on Figure 3.2. There, the partial wavelet coherencies are plotted as 2-dimensional heat-maps, where warmer colors represent higher coherences (unity coherence is depicted in red, and nearly null coherences in blue). The cone of influence, region subject to edge effects, is shown with a black line. In the partial phase-difference and gain diagrams, we display mean values corresponding to three frequency intervals: 2~4 days (short cycles), 4~8 days (medium-term fluctuations) and 8~16 days (long-run relationships). To prevent edge effects, each analysis begins when the related COVID-19 series presented the first non-null data. Also, for Hubei cases and deaths (not Shown) and for China deaths (Figure 3.2.b) the analysis ends when a zero-reported number have occurred the first time.

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

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

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

Figure 3.1 – Cumulative return on Brazilian stock market, IBOV, and its sector indices, and COVID-19 numbers worldwide.



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

Table 3.1 – Brazil stock market and COVID-19 numbers worldwide.

		COVID-19 variables															
		Deaths								Cases							
		US	World	China	Hubei	Italy	France	UK	Brazil	US	World	China	Hubei	Italy	France	UK	Brazil
Panel A. Dissimilarities																	
IBOV		.33***	.47*	.31*	.32*	.44**	.67	.42**	.59	.33***	.39**	.67	.49	.36***	.55	.44**	.39**
Panel B. Granger causalities																	
IBOV mean	COVID → Index	(.84)	(.91)	(.64)	(.87)	(.12)	(.38)	(.11)	(.00)***	(.50)	(.59)	(.03)**	(.20)	(.18)	(.63)	(.14)	(.84)
	Index → COVID	(.25)	(.77)	(.44)	(.40)	(.80)	(.63)	(.28)	(.09)*	(.06)*	(.40)	(.08)*	(.23)	(.01)**	(.25)	(.24)	(.01)**
IBOV quantil 0.10	COVID → Index	(.20)	(.16)	(.11)	(.99)	(.19)	(.19)	(.01)**	(.02)**	(.16)	(.16)	(.16)	(.08)*	(.27)	(.21)	(.16)	(.19)
	Index → COVID	(.01)**	(.16)	(.15)	(.53)	(.51)	(.01)**	(.09)*	(.03)**	(.01)**	(.01)**	(.01)**	(.08)*	(.01)**	(.39)	(.08)*	(.01)**
IBOV quantil 0.90	COVID → Index	(.03)**	(.02)**	(.04)**	(.05)**	(.03)**	(.03)**	(.03)**	(.03)**	(.03)**	(.02)**	(.02)**	(.08)*	(.03)**	(.02)**	(.02)**	(.03)**
	Index → COVID	(.31)	(.02)**	(.15)	(.62)	(.09)*	(.69)	(.47)	(.37)	(.06)*	(.07)*	(.43)	(.08)*	(.99)	(.01)**	(.06)*	(.04)**
Panel C. Coronavirus Disease																	
Lethality (deaths to cases)		4.8%	4.9%	5.5%	6.6%	14.5%	15.3%	14.0%	4.3%	-	-	-	-	-	-	-	-
Mortality (deaths per million inhabitants)		384.6	65.5	3.2	76.3	575.6	455.8	644.0	280.1	-	-	-	-	-	-	-	-
Total deaths (thousands)		127.4	511.3	4.6	4.5	34.8	29.8	43.7	59.6	-	-	-	-	-	-	-	-
Mean (Daily Log Growth - 7 Days Mov. Aver.)		4.2%	3.3%	-0.7%	-1.2%	1.2%	0.9%	2.2%	3.9%	5.9%	3.5%	0.0%	-2.8%	1.4%	3.5%	3.8%	5.4%
St. dev. (Daily Log Growth - 7 Days Mov. Aver.)		10.8%	8.2%	9.5%	8.4%	11.8%	23.0%	10.2%	7.6%	14.5%	10.4%	16.3%	16.4%	9.6%	34.0%	13.0%	9.7%

Notes: Data from January 31 to July 31, 2020. Dissimilarities between IBOV and the explanatory variables (deaths and cases of COVID-19). * p-value < 0.10, ** p-value < 0.05 and *** p-value < 0.01, derived from Monte Carlo Simulations with 5000 runs assuming red noise as a null hypothesis. Granger-causality in quantiles are based on Troster (2018). We perform the quantile regression with 3 lags of the dependent variable. P-value reported in the parenthesis. Source: Investing.com and Johns Hopkins Corona Virus Research Center

Figure 3.2 – Partial wavelet framework of IBOV vs COVID-19 controlled by first and second lag of IBOV and S&P Global 1200.

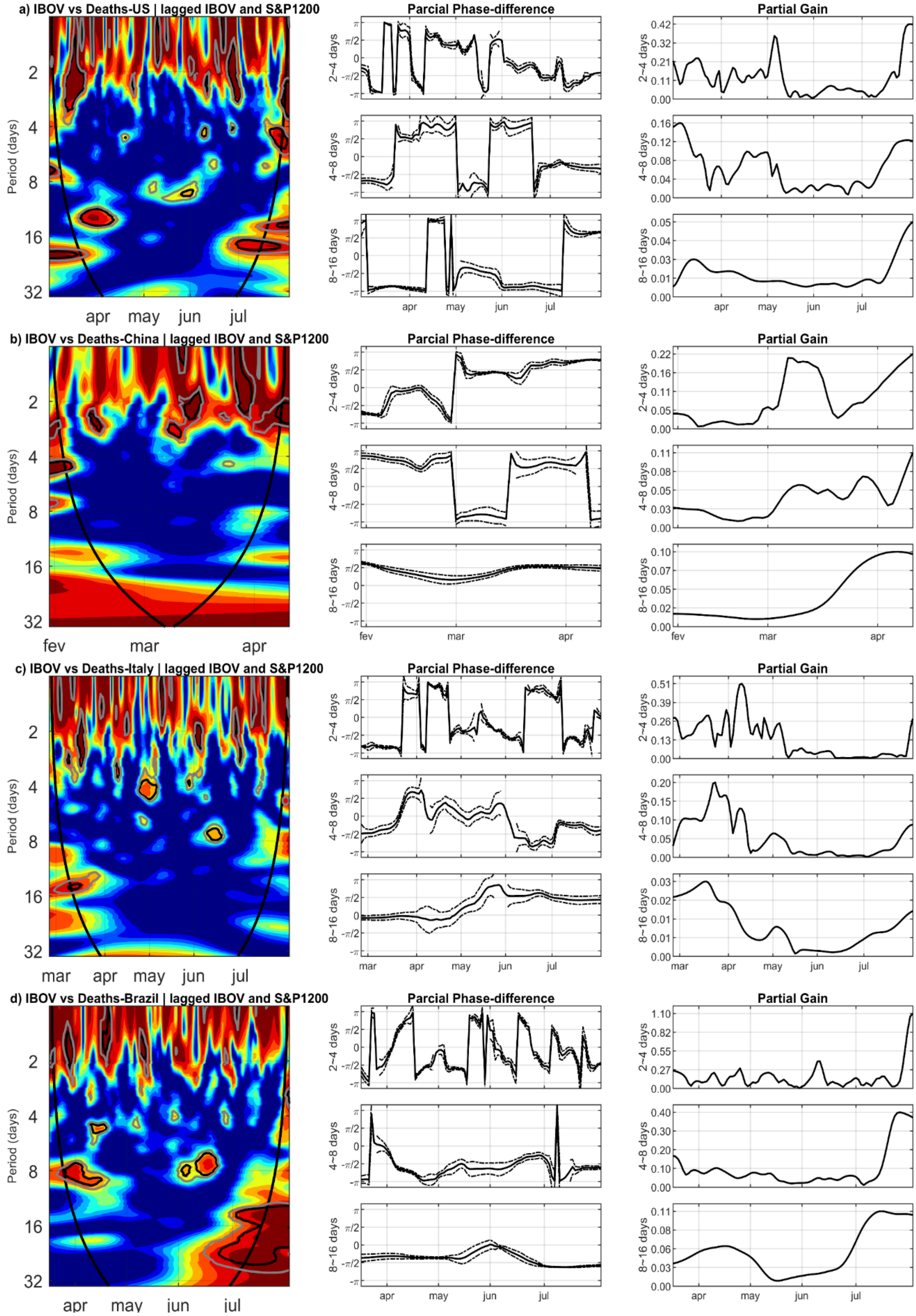


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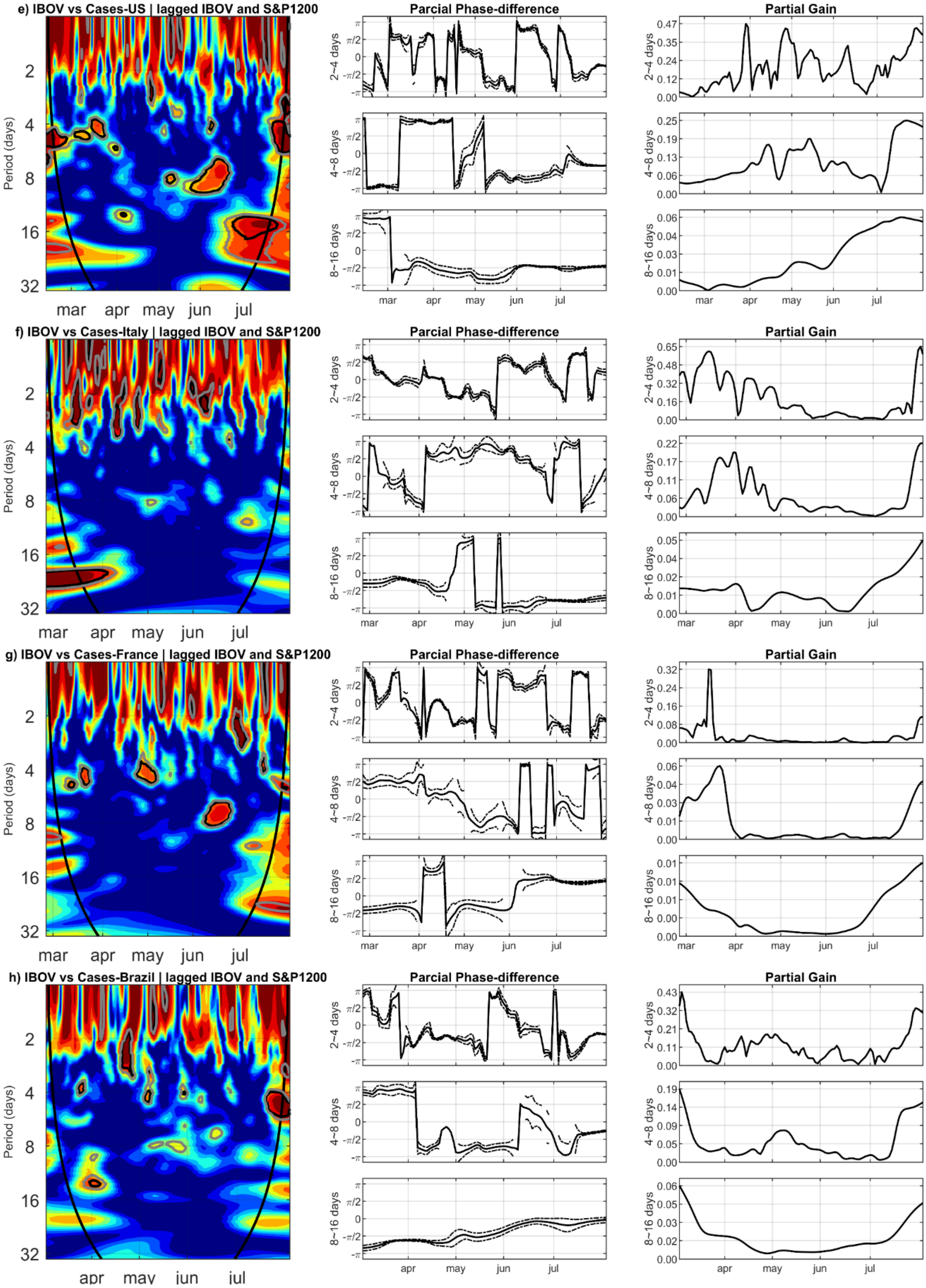
Figure 3.2 – Partial wavelet framework of IBOV vs COVID-19 controlled by first and second lag of IBOV and S&P Global 1200.



Notes: The cone of influence is shown as the black convex curve. The 5% significance level contours are in black, the 10% in gray and both are derived from Monte Carlo Simulations with 5000 runs assuming red noise as a null hypothesis. Data from January 31 to July 31, 2020. Source: Investing.com and Johns Hopkins Corona Virus Research Center.

Taking US deaths, reported in Figure 3.2.a, looking at the high frequencies (band of 2~4 days), we find a first very important strong and significant partial coherence region covering most of second half of March. In the corresponding time-frequency region the partial phase-difference shows signs of instability, assuming values either near $-\pi$ or near π, being the latter prevalent, meaning that for the entire time span analyzed IBOV and US deaths experienced an anti-phase relation and for the most part US deaths lead the Brazilian stock market index. Put in another way, returns on IBOV responded negatively (positively) to the news of increase (decrease) of deaths in the US occurred in the day before. During this time, we can also observe the formation of a local maximum in the partial gain function, at about 22%. This period happens to match the most grueling time in the entire COVID-19 pandemic for the stock market (In Brazil and elsewhere), when bottoms were being reached, after what the partial recovery has been observed.

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

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

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

Progressing in the analysis of the first exercise, once again with US deaths (Figure 3.2.a), we observe yet in the 2~4 days frequency band a high and significant spot around the end of June. There the phase-difference is little less than $-\pi/2$ (antiphase and IBOV leads). The gain is about 5%. Figure 3.1.b shows this period match the beginning of a somewhat relevant recrudescence in deaths in US soil which may have prompted attention of investors. US deaths also shows significant spots over the highest frequency (period < 2 days), towards the end of sample over the 4~8 days band and at three different moments in time in the 8~16 days band. For brevity we are not going to analyze them separately.

For China deaths (Figure 3.2.b), besides the critical region already analyzed, we highlight a small spot of significant partial coherence in mid-February, with a phase-difference of little less than zero (deaths in China leads in phase) and a very small gain of less than 1%. At this point in time the world deaths are almost all concentrated in China, but it is already possible to see some cases in Europe, what may have alerted the most risk averse individuals.

As For Italy deaths (Figure 3.2.c), the biggest spots of significant partial coherence are located in the end of April (phase difference of zero, in phase, move together) and mid-June (phase difference between $-\pi/2$ and $-\pi$, IBOV leads, out of phase movement) both in the 4~8 band.

Analyzing the Brazilian deaths (Figure 3.2.d) series, the most relevant points not yet discussed is a big significant area on the longest terms (8~16 days and over 16 days periods) toward the end of sample with phase-difference in the third quadrant (IBOV lead in antiphase) and a gain of 11%.

For US cases (Figure 3.2.e), by far the cases series with the most significant area on the partial coherence heatmap, we highlight the occurrence of a big significant area spanning both 2~4 and 4~8 days frequency bands and beginning at the second half of May lasting approximately one month. In both frequency bands the movement is led by IBOV in an antiphasic way. This first noteworthy region is followed in time by a cluster even bigger of high and significant partial coherence in lower frequencies. These two regions together occur, as reported before on the analysis of the US death series (Figure 3.2.a), during a noticeable recrudescence of deaths in US, what may have reflected in an increase of awareness for US of deaths and cases.

Italy cases (Figure 3.2.f) show a series of spots on short cycles and a big coherence area in the beginning of sample and the slowest frequencies. France cases (Figure 3.2.g) have three good sized spots of significant partial coherence concentrated on 4~8 days frequency bands. And finally, Brazil cases (Figure 3.2.h) shows the biggest spots in short and midterm frequency bands during second half of April and towards the end of the sample, respectively.

Also, in the Table 3.1 (Panel B), we report the p-values of the test for Granger-causality in mean (Granger, 1969), and in quantiles (Troster, 2018) to considers the pattern of dependence in the conditional tails of the distribution. For the center of the distribution, there is no predictability between COVID-19 deaths and IBOV index, except for the relationship between Brazil deaths and IBOV, where we found bi-causality. The IBOV index leads changes in US, Italy and Brazil cases, and we find bi-causality between the Index and China cases. So, for the center of the distribution the Granger-causality analysis indicates that the COVID-19 outbreak has a limited effect on the Brazil stock market. However, the Granger-causality in mean possibly ignores the movements in the investors' perception of risk during different paths of the pandemic.

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

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

3.3.3 Brazilian sectorial contagion and pass-through

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

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

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

Initially we evaluate the evidence of sectorial contagion, defined, in line with Forbes and Rigobon (2002)[6], as the increase of cross-sector linkages among the returns on IBOV sector indices during the first semester of 2020 as compared to the last semester of 2019. This is performed first using the wavelet spectrum distance metric in time and frequency - dissimilarity - and reported in Table 3.2 (Panel D).

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

The maximum decrease in dissimilarity, with magnitude of 27.2%, was computed to a pair of sectors heavily regulated by government: Public Utilities (UTIL) – Electrical Energy (IEE). This decrease indicates that in 2020 the time and frequency content of the returns on these sector indices were much more alike, suggesting an increase in cross-sector linkages and therefore contagion. The maximum increase in dissimilarity, 10.2%, was relates to the pair comprised of the best and worst performing sectors during pandemic: Basic Materials (IMAT) - Real State (IMOB) (see Table 3.2, Panel A for summary statistics of the sector indices). This is a very intuitive result once these indices have arguably experienced opposite behavior during pandemic. Also, one can see that among all sectors, only Basic Materials (IMAT), the best performing index, have a smaller number of significant dissimilarities in 2020 as compared to 2019.

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

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

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[6] 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.

$$VaR(\alpha) = Io\Phi^{-1}(1-\alpha)\sigma_p \tag{3.7}$$

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

$$\sigma_p^2 = \sum_{i=1}^{n} w_i^2\sigma_i^2 + \sum_{i=1}^{n}\sum_{j=1,j\neq i}^{n} w_i w_j Cov(r_i, r_j) \tag{3.8}$$

In (3.8) w_i, σ_i, and r_i represents the weight of asset i in the portfolio, the asset i volatility and its returns, respectively. To compute the VaR in time frequency, we use the wavelet-based analog measures of variance and covariance in (3.8).

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

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

The Figure 3.3 shows the VaR ratio test performed, considering a portfolio formed by all 7 Brazilian sector indices under consideration at this paper[7]. Qualitatively, it is noteworthy the region of highest ratio clustered from the first days of February to the end of Mach, 2020, the most difficult period for the stock market, and practically crossing all the frequencies. Also, one can see that 2020 shows overall much warmer colors in comparison to 2019, reflecting a higher mean ratio, and, thus, increased linkages.

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

Overall, these results reinforce the evidence of presence of contagion in between the Brazilian sectors during COVID-19 pandemic. Regarding the pass-through in the Brazilian economy, we perform Granger causality tests based on VAR among the sector indices, conditional to the two first lags of IBOV and S&P Global 1200. The p-Values of the tests are reported on Table 3.2 (Panel C).

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

Table 3.2 – Summary statistics, dissimilarities and Granger causality of S&P 500 and its sector indices.

Panel A: Summary statistics of Brazil sector indices

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

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

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

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

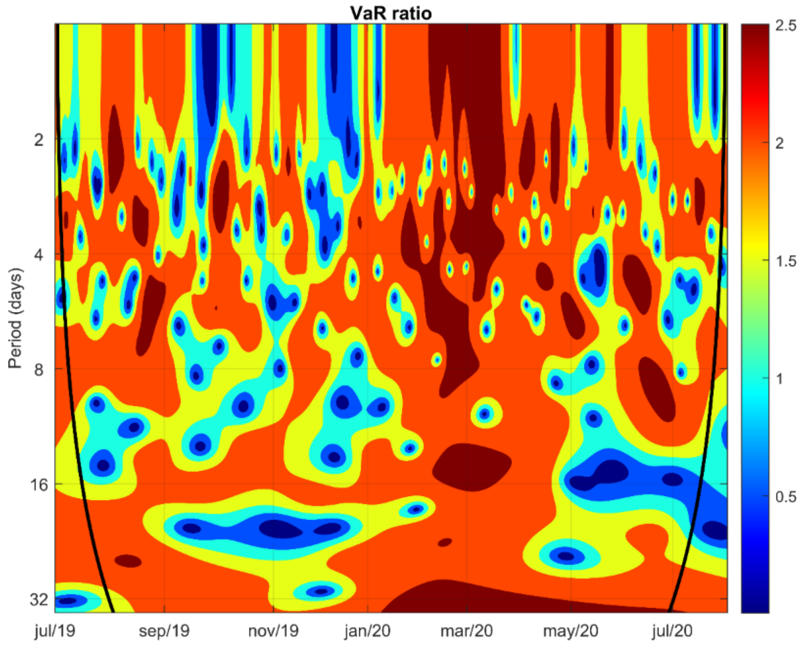
Indices	IMAT	IEE	INDX	ICON	IFNC	UTIL	IMOB
Basic Materials (IMAT)		0.95	0.72	0.30	0.89	0.78	0.53
Bovespa Electrical Energy (IEE)	0.31		**0.01**	**0.03**	**0.06**	**0.09**	**0.00**
Bovespa Industrial Sector (INDX)	0.43	0.61		0.31	0.52	0.38	0.47
Consumption (ICON)	0.99	0.93	0.45		0.62	0.82	0.74
Financials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

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

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

Notes: Panel D uses data from July to December, 2019 and from January to June, 2020. The remaining data is from January 22 to July 31, 2020. Dissimilarities between IBOV and the explanatory variables (deaths and cases of COVID-19). * p-value < 0.10, ** p-value < 0.05 and *** p-value < 0.01, derived from Monte Carlo Simulations with 5000 runs assuming red noise as a null hypothesis. Granger-causality based on a conditional VAR, the number of lags is set by HQ criteria (max lags= 5). P-values are reported (values less than .10 in Bold). Source: Investing.com and Johns Hopkins Corona Virus Research Center.

Figure 3.3 – Ratio between the VaR of an equally weighted portfolio of Brazil sector indices with and without co-movement.



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

3.4 Conclusion

We fill the gap of the COVID-19 literature by studying the conditional relations in the time-frequency domain between the cases or deaths by COVID-19 in Hubei, China, in countries with record deaths and in the world and the return on Brazilian broad stock market index, IBOV, from January 22 to July 31, 2020.

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

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

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

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

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4 ON THE RISK-BASED CONTAGION OF G7 BANKING SYSTEM AND THE COVID-19 PANDEMIC

4.1 Introduction

The discussion on the long run and short run linkages among financial markets suggests the relevance of monitoring banking systems around the world, mainly during periods of crisis. This economic sector is one of the most vulnerable due to contagious effects,[8] and we should be aware of the consequent economic impacts of chaos on the banking system. First, banking crises are costly, and a great deal of prudential effort is undertaken to avoid them. Bordo et al. (2001) estimate losses of around 6% of GDP due to banking crisis in the last quarter of the 20th century, while Laeven and Valencia (2013) report losses of about 30% of GDP during the global financial crisis in 2007. Second, according to OECD (2012), financial contagion shocks increase countries' risk of suffering an economic crisis: annual crisis probability is slightly above 1% without financial contagion and more than 28% in periods with financial contagion.

Regarding the current global pandemic, Goodell (2020) claims that the main concerns arise from rising costs for health systems, loss of job productivity, social distance that disrupts economic activity, depressed tourism and impacts on foreign direct investment. Some of these phenomena are idiosyncratic, and they seem to be able of generating uncertainties that are impacting the global financial markets very strongly.

Concerning banking systems, on the one hand, Aharony and Swary (1983) find that failures of a dishonestly run banking institution, such as fraud and internal irregularities and even a large bank, need not cause panic and loss of public confidence in the integrity of the banking system as a whole. However, when there are macro fundamentals, banking crises are overwhelmingly associated with the presence of both systematic and idiosyncratic contagion (Dungey and Gajurel, 2015). Unfortunately, we are experiencing the second scenario: a crisis characterized by complex economic fundamentals and difficult to predict.

Fortunately, there is already some literature on contagion between sectors, and specifically the banking sector during this pandemic. Matos, Costa, and da Silva (2021) propose assessing the conditional relationship in the time-frequency domain between the return on S&P 500 and the cases or deaths by COVID-19 in Hubei, China, countries with record deaths and the world, for the period from January 29 to June 30, 2020. They find that short-

[8] For instance, Dungey and Gajurel (2015) identify international contagion in banking during this recent global crisis for more than 50 economies through one of the three channels: systematic, idiosyncratic, and volatility.

term cycles of deaths in Italy in the first days of March, and soon afterwards, cycles of deaths in the world can lead out-of-phase US stock market. They also report that find that low frequency cycles of the US market index in the first half of April are useful to anticipate in an anti-phasic way the cycles of deaths in the US. Concerning the sectoral contagion, they find that the energy sector seems to be the first to react to the pandemic, and that the predictability of the Telecom cycles are useful to tell the history of the pass-through of this recent health crises across the sectors of the US economy.

Costa et al. (2020) find widespread contagion among the financial sector of G7 countries during the COVID-19 crisis particularly in scales of over 16 days, based on wavelet coherence. They also find that COVID-19 can explain part of the lower frequency contagion. We add to this discussion, addressing the risk side of banking system during crisis. Possibly, the study conceptually closest to ours is de Jesus Filho, Matos, and Fonseca (2020). They propose an innovative measure of Value-at-Risk (VaR) based on time-varying moments of the best fitting probability distribution function (pdf). This risk measure can capture the cross-effects associated with contagion and integration through the estimation of a multivariate ARMA-GARCH. They implement an empirical exercise to account for the risk management of some of the main worldwide financial sector indices of G20 economies, and they find that according to some informative backtesting, their innovative VaR seems to perform better than Basel VaR. They claim that to ignoring cross-effects may be unsuitable for some specific samples of assets due to effects of interdependence between financial markets.

We are the first, to our knowledge, to propose a risk-based analysis, by comparing the current pandemic period and the previous period of stability. We also contribute by exploring sectoral level data and using novel methodological approach, using wavelet-based tools. The analysis is based on the comparison of statistical metrics, as drawdown, or best fitting probability distribution function VaR, and on the analysis of wavelet dissimilarities and frequency-based Granger's causalities. Moreover, we also analyze VaR ratio considering whether there are co-movements between pairwise of banking systems. In this sense, we are aligned methodologically to Rua and Nunes (2009). We use daily returns on G7 financial sector indices: S&P 500 Financials (US), CAC Financials (France), S&P/TSX Canadian Financials (Canada), DAX Financial Services (Germany), FTSE 350 Financial Services (UK), FTSE Italia All Share Financials (Italy), and Nikkei 500 Other Financial Services (Japan). We used local currencies following Wang et al (2017) and Mink (2015). The data covers the period from January 01, 2015 to December 31, 2019 (pre-crisis), and the period from January 01, 2020 to October 16, 2020 (pandemic crisis). We use this period because it comparable in length to the studies of contagion performed with wavelet as in Gallegati (2012) and because it provides both a relative stable and long enough pre-crisis period to be considered a baseline while allowing including the very last data in the COVID-19 crisis.

The layout of the study is the following. The first section provides an introduction, with the backdrop and status of research topic. The second section provides the review of the most related literature. The third section presents the objectives of the study and the rationale underpinning the study. The fourth section describes the methodology used and provides the data source, while the fifty presents the results and its discussions. Conclusions and managerial implications are in sixth section which is followed by the last section containing suggestions for future works.

4.2 Literature Review

The contagion definition and the identification of factors that contribute for the systemic risk has been widely considered source of debate in the financial literature. Moser (2003) emphasize the central role to distinguish common (or coincident) shocks which can cause financial turmoil (spillovers episode) of a specific shock in one market (or a subset of markets) that spreads to other markets during distress periods (contagious episode). From this distinction, we highlight two complementary definitions of contagion. First, contagion can be seen as one episode where the advent of a crisis in one market (or subset of markets) causes an increased likelihood of financial turmoil in other markets (Kaminsky and Reinhart, 2000). Second, contagion is one situation where a specific shock in one market (or a subset of markets) causes a significant increase in cross-market linkages (Forbes and Rigobbon, 2002). Rigobbon (2019) named this definition as “shift contagion”.

We follow both definitions and we assess whether the propagation of the shocks in the international financial sector was intensified during the Covid-19 outbreak. To do this, we split the sample between tranquil and turbulent times.

The theorical literature points out some reasons for the propagation mechanism in banking sector specifically. The common lender assumption postulates the financial market imperfections as financial contagion source in turmoil periods. In this theory, the transmission of shocks among countries may be associated with the fact that they share the same lenders (Kaminsky and Reinhart, 2002). In this sense, a crisis that increases the default risk in one of debtor countries can cause a reduction in the services offers by lender for the other countries.

Pavlova and Rigobon (2008) find out a considerable effect on market co-movements in periods where center’s agents (lenders) face portfolio constraints. As a specific example, Kaminsky and Reinhart (2002) have pictured the financial turmoil in Japan as source of financial contagion on the Asian markets in 1997.

The liquidity problem is other theorical possibility for the occurrence of financial contagion. In this sense, the turbulence in one country decreases the market value of the intermediaries' portfolio, generating a run for liquidity on the capital market (Jokippi and Lucey, 2007). The initial turmoil may induce investor to sell off their holdings through the markets putting pressure on the international asset prices exacerbating the propagation mechanism of shocks.

A third theorical current concerns with the role of coordination view on the contagion path through. Calvo and Mendoza (2000) evaluates the effect of informational problem on investor behavior. The authors point that international information asymmetry can drive the removal of resources from investors across countries. Matos, Costa, and da Silva (2021) support the presence of this movement in the beginning of the coronavirus pandemic.

Regarding additional empirical investigations, Rajwani and Kumar (2016) verifies financial contagion from the US on the Asian markets between 2007 and 2010. The authors point out that the sub-prime crisis spread the propagation shocks across the Asian countries. In the same perspective, Raiwani and Kumar (2019) add that this financial contagion among US and Asian markets is non-linear with tail dependence in extreme deviation on returns. Elliot, Golub and Jackson (2014) highlight the international financial networks as an important channel for contagion.

Endogeneity, non-linearities, conditional heteroskedasticity and short live of contagion events are the main limiting factors from an empirical point of view (Rigobon, 2019). To overcome these limitations, methods as Dynamic Conditional Correlation-GARCH (Hung, 2019; Gamba-Santamaria et. al, 2017) and reduced form of generalized vector autoregression (Diebold amd Yilmaz's, 2012; Akhtaruzzaman, Boubaker and Sensoy, 2021) have been applied to consider time-variant processes and heteroskedastic in data in the former and to control the endogeneity in the latter.

4.3 Research Objectives and Rationale

The COVID-19 pandemic, albeit a unprecedent disaster from mankind standpoint, provides a unique backdrop for studying how the links between specific sectors of international markets behave under extremely stressful moments. We aim to investigate the evolution of this link in, arguably, one of the most vital sectors for the orderly functioning of the markets as a hole, the banking sector. We focus on the G7, the set of the seven largest economies, due to their centrality and relevance in the Global picture.

Studying the links of a specific sector during a crises moment, we further evidence the presence of financial contagion - well presented in Forbes and Rigobon (2002) -, phenomenon of major consequences in terms of asset allocation and risk management.

So far, the studies have focused on more traditional econometric approaches, as the Dynamic Conditional Correlation of Engles (2002) and the forecast error variance decomposition based derived of Dyebolt and Yulmaz (2009). Also, the literature is scarce in the sectoral level, as discussed in Mensi et al. (2020).

Thus, we contribute to the existing literature by using the banking sectoral data encompassing the COVID-19 pandemic and also by bringing, in addition to traditional measures of risk, novel methodological framework -namely, the wavelet-based tools - that enable to detect heterogeneous behavior along the time and frequencies. This addition is of particular relevance in financial markets, considering a diversity of investors profiles, working with aims in different time horizons.

In particular, we use discreate and continuous wavelet tools to identify the transmission mechanisms in the time and frequency domain. The flexible resolution of time/frequency space of the wavelet turn the evidence related robust to regime switching, structural breaks, outliers, and shocks of large memory (Rua, 2012; Behmad, 2013), turning the method suitable to study the high frequency co-movements as in the present case.

4.4 Methodology

The first part of our empirical analysis is based simply on the comparison of risk metrics, obtained for the pre-crisis and the period during the current crisis. We observe the standard deviation, semi-variance, drawdown, semi kurtosis and value at risk, based on Matos et al. (2015).

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

According to Aguiar-Conraria et al. (2018), the continuous wavelet transform of a time series $y(t)$ is given by

$$W_y(\tau,s) = \frac{1}{\sqrt{|s|}}\int_{-\infty}^{\infty} y(t)\,\bar{\psi}\left(\frac{t-\tau}{s}\right)dt \tag{4.1}$$

Where $\bar{\psi}$ represents the complex conjugation of the mother wavelet used.

In each position in the time-frequency plane the Wavelet Power Spectrum (WPS) can be measured as the squared absolute value of the wavelet transform, representing a time-frequency measure of variance:

$$WPS_y(\tau,s) = \left|W_y(\tau,s)\right|^2 \tag{4.2}$$

Considering now a pair of time series, $y(t)$ and $x(t)$, a covariance time-frequency measure is denominated Cross-Wavelet Transform:

$$\mathrm{W_{yx}(\tau,s) = W_y(\tau,s)}\overline{W_x}(\tau,s) \tag{4.3}$$

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

$$dist(W_x,W_y) = \frac{\sum_{k=1}^{K} w_k^2[d(\mathrm{l}_x^k,\mathrm{l}_y^k)+d(\mathbf{u}_k,\mathbf{v}_k)]}{\sum_{k=1}^{K} w_k^2} \tag{4.4}$$

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

We also measure the casual relationship among financial sectors comparing before and after the crisis in different frequencies, using wavelet-based Granger causality test, following Sharif et al. (2020). The test consists in applying discrete wavelet filtering to the original series and using the obtained components in frequencies (2-4 days, 4-8 days and so on) as inputs to a standard Granger (1969) tests in a mean. Under the null hypothesis of no causality in the given frequency, the test statistic provides asymptotic x^2 p-values. In this work, we use Maximal Overlap Discrete Wavelet Transform (MODWT) as the filtering technique. For a full description of this technique, refer to Percival and Mofjeld (1997).

Finally, in our main exercise, we use the wavelet-based Value at Risk (VaR) ratio shown in Rua and Nunes (2009). The VaR of a portfolio in the 1- α confidence level can be defined in the following manner:

$$VaR(\alpha) = Io\Phi^{-1}(1-\alpha)\sigma_p \tag{4.5}$$

where Io represents the initial investment, $\Phi(.)$ the cumulative distribution function of the standard normal, and σ_p the portfolio volatility. The VaR should be understood as the maximum loss to be expected of a portfolio with a certain level of confidence, being a widespread measure of risk.

Assuming a portfolio with n assets, its variance, σ_p^2, can be computed as follows:

$$\sigma_p^2 = \sum_{i=1}^{n} w_i^2 \sigma_i^2 + \sum_{i=1}^{n} \sum_{j=1, j\neq i}^{n} w_i w_j Cov(r_i, r_j) \tag{4.6}$$

In (4.6), w_i, σ_i, and r_i are the weight of asset i in the portfolio, its volatility, and its return, respectively.

As one can see, the portfolio variance has two terms, 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 (4.6) and the variance computed excluding the covariance terms in (4.6).

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 even when controlling by individual component risks.

However, we do not use time series expressions for computing (4.6), but instead we use time-frequency domain wavelet-based analog measures of variance and covariance. Thus, we use the Wavelet Power Spectrum and Cross-Wavelet Transform described in (4.2) and (4.3) respectively. This procedure allows us to observe how the connections have changed in time and frequency through 3 dimensional maps.

4.4.1 Data source

Our data is comprised of daily percent returns of G7 financial sector indices from January 01, 2015, to October 16, 2020. Namely, we use S&P/TSX Canadian Financials (Canada), CAC Financials (France), DAX Financial Services (Germany), FTSE Italia All Share Financials (Italy), Nikkei 500 other financial services (Japan), FTSE 350 Financial Services (UK), and S&P Financials (US) indices.

All data have been gathered from Investing.com.

4.5 Results and Discussion

Figure 4.1 shows cumulative nominal return on financial sector indices in terms of the local investor´s currency, based on the daily time series for the end-of-day quote, from January 01, 2015, to October 16, 2020.

Over the period from 2015 to 2019 – characterized by a period without crisis by NBER –, only the Italian banking sector recorded a cumulative loss of 13.2%, as a result of a downward trend during the mid-2015 period to mid-2016. The other banking indices showed cumulative gains, ranging from 9.7% in Japan to 123.1% in Germany. This German banking sector is the only one diverging from the others.

The cumulative return in the year 2020, however, suggests a pattern with very sharp accumulated declines from the second half of February, again with divergence from the German banking sector, from the second half of March 2020. DAX Financial Services is the only one that registered a cumulative return from January 1, 2020, to October 16, 2020, exceeding 5%.

Concerning these time series, they are not Gaussian but rather driven by Laplace and Generalized extreme value, among other pdf. Moreover, Matos, da Silva and Oliveira (2019) find that they share an equilibrium relationship so that they cannot move independently in the short- and long-run, and according to Matos, Benegas and Costa (2019), those indices seem to be generated from a nonlinear and nonchaotic system, based on BDS test and the Lyapunov exponent.

We report main statistics on risk in the Table 4.1.

The analysis of the standard deviation during the pre-pandemic period and during the pandemic suggests an increase in all G7 indices, and this relative increase is smaller in Japan and Italy, and higher in Canada and US. We find a similar pattern based on the semi-variance. Among the countries with the greatest increase in risk, only US was severely affected by cases and deaths by COVID-19. The VaR obtained from the quantile function extracted from the best fitting distribution, following Matos et al. (2015) suggests that there are banking sectors with more comfortable risk management, as in Germany, while in the US and France, this metric increased by more than 4% in the pandemic.

The analysis based on the drawdown shows a concern about the worst cumulative fall in the banking system in France, a country strongly affected by the deaths by COVID-19. There is also evidence of a reduction in the drawdown recorded in the pandemic compared to that seen in the period from 2019 to 2019 in Italy and Germany. The German banking sector showed the greatest increase in semi kurtosis, while the banking sectors in France, UK, Italy and Japan had a reduction in this unilateral fourth-order moment.

Concerning this concept of dissimilarity, given that we use the Hermitian angle, the highest value the distance can take is $\pi/2$, while a value very close to zero means that two countries have a very similar wavelet transform, or they share the same high-power regions and also that their phases are aligned. In other words, the contribution of cycles at each frequency to the total variance is similar between both countries.

According to the dissimilarities reported in Table 4.2, considering the frequency from 1 to 64 days, in the pre-pandemic period, of the 21 possible pairwise combinations, only 3 were significant. In 2020, the pandemic seems to have intensified this metric of contagion. There are now 18 possible significant pairwise combinations. The only 3 non-significant combinations are associated with the banking sector in Japan, a country little affected by COVID-19. We may infer that in 2020 the ups and downs of each G7 banking cycle occur simultaneously in both countries, except for Japan vs UK, US and Canada. During the pre-pandemic period, the average dissimilarity was 0.51, while in 2020, the average was 0.30; a reduction of 42.1%.

In terms of causality, the results of the original test (Table 4.3) suggest that among the 42 possible combinations involving the G7 banking systems, there are 23 combinations without causality in the pre-pandemic period, while during the pandemic there are only 14 without causality. Only in the frequency of 16 ~ 32 days, we find more causalities in the period from 2015 to 2019, than in 2020. It is important to highlight that the banking contagion in 2020 measured by causality seems to be stronger and more widespread in the lowest frequency, 32 ~ 64 days. We find 39 combinations with significant causality at 5%, among 42 possible ones. Due to the fast reaction of the financial system, the most relevant causality is based on the highest frequency, 2 ~ 4 days. Japanese banking cycles have always been influenced by banking cycles in other G7 countries, before and during the pandemic. The interesting difference is the increase of the predictive power of banking cycles in the US and especially in the Italian banking system. In the pre-pandemic period, Italian banking cycles were able to anticipate only Canadian and Japanese cycles. During the pandemic, Italian cycles came to be useful in predicting banking cycles in all other G7 economies. We remember that Italy was the first developed economy to suffer more strongly from the effects of COVID-19, in cases and deaths.

Figure 4.1 – Cumulative return on financial sector indices (G7).
Figure 4.1.a – Pre-crisis period (01.01.2015 – 31.12.2019)

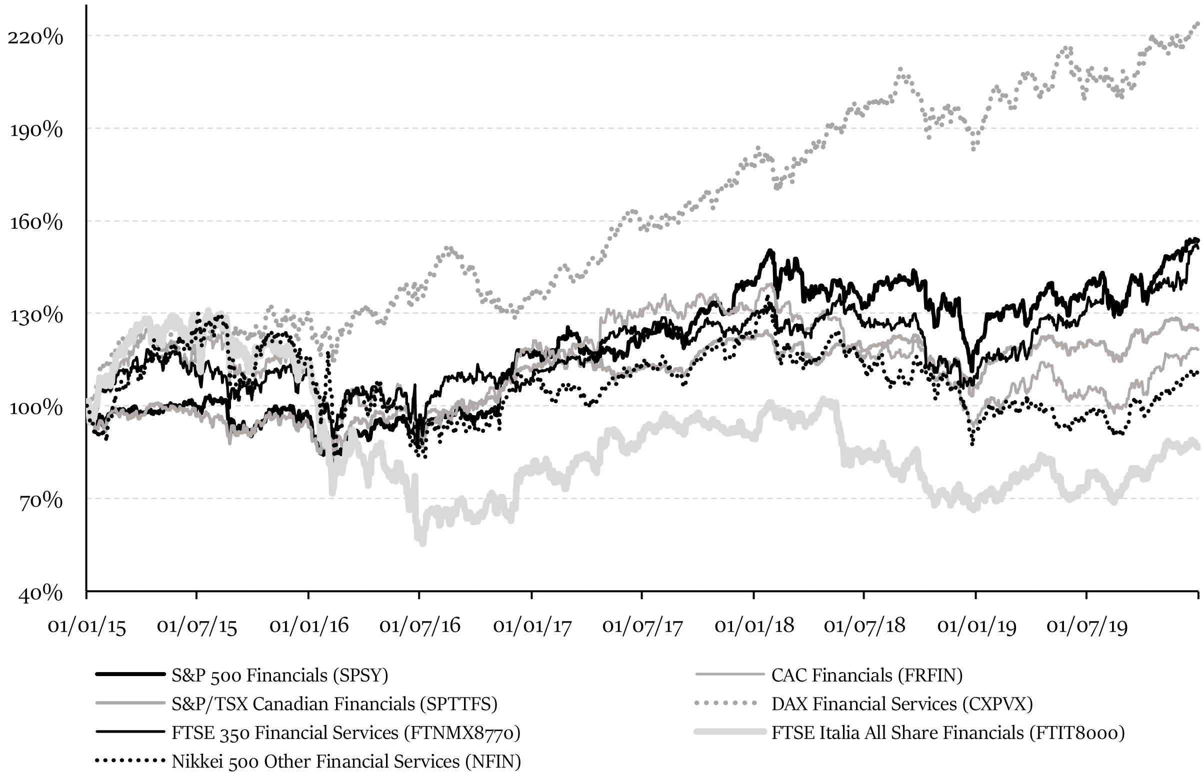
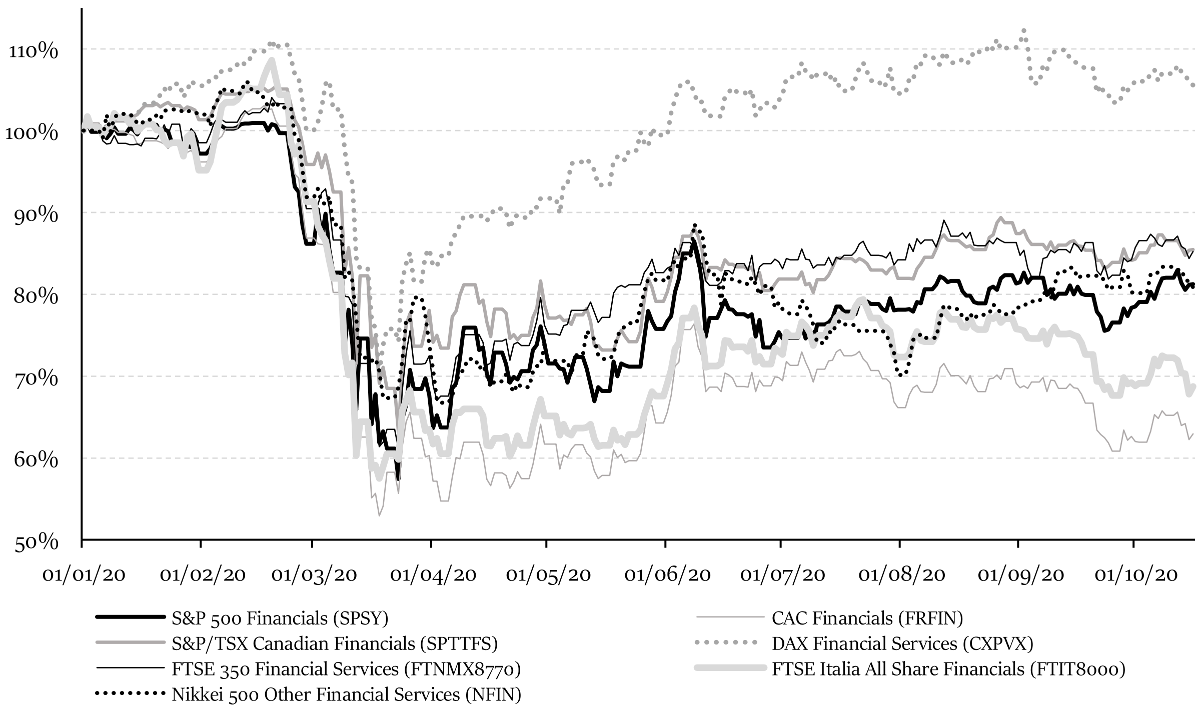


Figure 4.1.b – Pandemic period (01.01.2020 – 16.10.2020)



Notes: Data from January 01, 2015 to October 16, 2020. Source: Authors' own findings.

Table 4.1 – Summary statistics on risk

Statistics	Period	Standard deviation	Semivariance	VaR (99%)	Drawdown	Semikurtosis
S&P 500 Financials (SPSY)	01-jan-15 to 31-dec-19	0.89%	0.65%	-2.72%	34.92%	5.15
	01-jan-20 to 15-oct-20	2.59%	1.88%	-7.21%	43.12%	6.32
CAC Financials (FRFIN)	01-jan-15 to 31-dec-19	0.97%	0.71%	-2.34%	33.25%	14.86
	01-jan-20 to 15-oct-20	2.32%	1.75%	-6.54%	48.66%	8.90
S&P/TSX Canadian Financials (SPTTFS)	01-jan-15 to 31-dec-19	0.60%	0.44%	-1.23%	19.74%	4.47
	01-jan-20 to 15-oct-20	2.27%	1.63%	-4.04%	40.15%	8.04
DAX Financial Services (CXPVX)	01-jan-15 to 31-dec-19	0.82%	0.57%	-2.03%	55.32%	3.48
	01-jan-20 to 15-oct-20	1.56%	1.17%	-3.03%	36.65%	9.68
FTSE 350 Financial Services (FTNMX8770)	01-jan-15 to 31-dec-19	0.96%	0.71%	-2.28%	33.79%	15.99
	01-jan-20 to 15-oct-20	1.90%	1.43%	-4.03%	41.29%	8.37
FTSE Italia All Share Financials (FTIT8000)	01-jan-15 to 31-dec-19	1.53%	1.10%	-4.22%	57.72%	15.88
	01-jan-20 to 15-oct-20	2.18%	1.70%	-5.22%	47.07%	13.58
Nikkei 500 Other Financial Services (NFIN)	01-jan-15 to 31-dec-19	1.26%	0.90%	-2.41%	36.12%	6.14
	01-jan-20 to 15-oct-20	1.66%	1.21%	-4.66%	37.03%	4.01

Source: Authors' own findings.

Table 4.2 – Dissimilarities [1 ~64 days]

Indices	SPSY	FRFIN	SPTTFS	CXPVX	FTNMX8770	FTIT8000	NFIN
S&P 500 Financials (SPSY)		0.28**	0.22**	0.29**	0.29**	0.26**	0.38
CAC Financials (FRFIN)	0.44		0.28**	0.31*	0.31*	0.15***	0.28**
S&P/TSX Canadian Financials (SPTTFS)	0.42**	0.46		0.24**	0.30*	0.28**	0.37
DAX Financial Services (CXPVX)	0.59	0.50	0.60		0.22***	0.29**	0.32*
FTSE 350 Financial Services (FTNMX8770)	0.52	0.43**	0.55	0.51		0.31*	0.39
FTSE Italia All Share Financials (FTIT8000)	0.52	0.33***	0.53	0.56	0.48		0.31**
Nikkei 500 Other Financial Services (NFIN)	0.53	0.49	0.51	0.61	0.48	0.55	

Notes: Data from January 01, 2015 to December 31, 2019 (lower triangle) and from January 01, 2020 to October 16, 2020 (upper triangle). * p-value < 0.10, ** p-value < 0.05 and *** p-value < 0.01, derived from Monte Carlo Simulations with 3000 runs assuming red noise as a null hypothesis. Source: Authors' own findings.

Finally, we know that the portfolio variance can be decomposed in two factors linked to variance and covariance of pairs of assets. The ratio between the variances of the portfolio with and without assuming co-movement brings information about how much linkage there is among the assets comprising the portfolio. In other words, analyzing how this ratio evolve in the time-frequency plain can show if there is evidence of contagion (increase in linkage) among the components of the portfolio. Figure 4.2 reports the squared VaR Ratio taking into account for an equally weighted portfolio of G7 financial sector portfolio, with and without co- movement. Numerically, before the pandemic period, the average of ratio (not squared) was 1.70, while throughout the year 2020 until October 15 this average was 2.05.

Considering the height of the pandemic (February and March, 2020), this average was 2.23. In both cases, there are increases of 21% and 31%, in relation to the period that anticipated the pandemic.

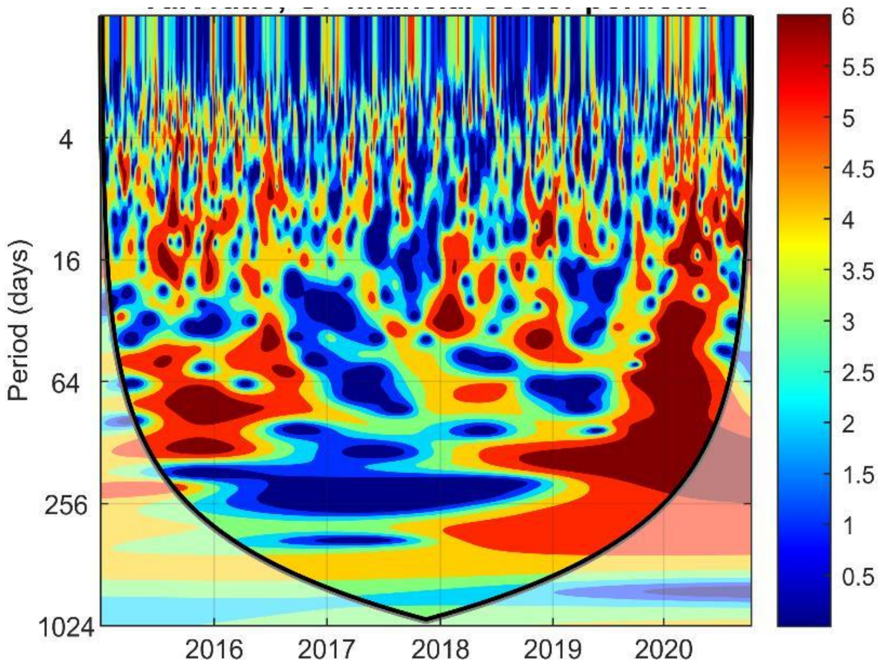
Table 4.3 – Frequency-based Granger causality on financial sector indices (G7)

	Pre-Crisis (01.01.2015 - 31.12.19)							Crisis (01.01.20 - 15.10.20)						
Traditional Granger causality	SPSY	FRFIN	SPTTFS	CXPVX	FTNMX8770	FTIT8000	NFIN	SPSY	FRFIN	SPTTFS	CXPVX	FTNMX8770	FTIT8000	NFIN
S&P 500 Financials (SPSY)		0.000	0.354	0.024	0.000	0.303	0.000		0.005	0.003	0.045	0.010	0.003	0.000
CAC Financials (FRFIN)	0.478		0.028	0.043	0.349	0.079	0.000	0.000		0.000	0.111	0.058	0.156	0.000
S&P/TSX Canadian Financials (SPTTFS)	0.331	0.001		0.051	0.000	0.005	0.000	0.094	0.000		0.000	0.000	0.001	0.000
DAX Financial Services (CXPVX)	0.379	0.031	0.001		0.131	0.001	0.000	0.001	0.596	0.000		0.193	0.374	0.000
FTSE 350 Financial Services (FTNMX8770)	0.629	0.033	0.134	0.120		0.005	0.000	0.030	0.252	0.001	0.290		0.129	0.000
FTSE Italia All Share Financials (FTIT8000)	0.788	0.213	0.162	0.081	0.764		0.000	0.000	0.000	0.000	0.000	0.003		0.000
Nikkei 500 Other Financial Services (NFIN)	0.146	0.475	0.303	0.261	0.815	0.278		0.364	0.041	0.068	0.361	0.426	0.003	
Granger causality [2 days ~4 days]	SPSY	FRFIN	SPTTFS	CXPVX	FTNMX8770	FTIT8000	NFIN	SPSY	FRFIN	SPTTFS	CXPVX	FTNMX8770	FTIT8000	NFIN
S&P 500 Financials (SPSY)		0.000	0.437	0.013	0.000	0.191	0.000		0.010	0.015	0.003	0.018	0.007	0.000
CAC Financials (FRFIN)	0.032		0.006	0.009	0.209	0.193	0.000	0.000		0.000	0.512	0.081	0.719	0.000
S&P/TSX Canadian Financials (SPTTFS)	0.107	0.000		0.014	0.000	0.008	0.000	0.058	0.000		0.000	0.000	0.003	0.000
DAX Financial Services (CXPVX)	0.405	0.162	0.001		0.038	0.233	0.000	0.003	0.562	0.000		0.108	0.806	0.000
FTSE 350 Financial Services (FTNMX8770)	0.063	0.084	0.037	0.157		0.023	0.000	0.108	0.188	0.006	0.450		0.280	0.000
FTSE Italia All Share Financials (FTIT8000)	0.342	0.231	0.032	0.064	0.684		0.000	0.000	0.005	0.000	0.043	0.023		0.000
Nikkei 500 Other Financial Services (NFIN)	0.001	0.009	0.193	0.358	0.106	0.005		0.476	0.004	0.047	0.556	0.453	0.002	
Granger causality [4 days ~8 days]	SPSY	FRFIN	SPTTFS	CXPVX	FTNMX8770	FTIT8000	NFIN	SPSY	FRFIN	SPTTFS	CXPVX	FTNMX8770	FTIT8000	NFIN
S&P 500 Financials (SPSY)		0.000	0.208	0.058	0.000	0.314	0.000		0.006	0.001	0.060	0.047	0.000	0.000
CAC Financials (FRFIN)	0.279		0.023	0.074	0.238	0.018	0.000	0.000		0.000	0.733	0.100	0.065	0.000
S&P/TSX Canadian Financials (SPTTFS)	0.128	0.003		0.003	0.002	0.291	0.000	0.012	0.003		0.000	0.000	0.000	0.006
DAX Financial Services (CXPVX)	0.573	0.893	0.000		0.852	0.018	0.000	0.011	0.166	0.003		0.023	0.275	0.000
FTSE 350 Financial Services (FTNMX8770)	0.352	0.174	0.126	0.166		0.006	0.000	0.037	0.249	0.004	0.307		0.035	0.000
FTSE Italia All Share Financials (FTIT8000)	0.468	0.039	0.051	0.041	0.440		0.000	0.000	0.016	0.000	0.301	0.032		0.000
Nikkei 500 Other Financial Services (NFIN)	0.000	0.000	0.002	0.227	0.005	0.000		0.194	0.009	0.263	0.578	0.426	0.000	
Granger causality [8 days ~16 days]	SPSY	FRFIN	SPTTFS	CXPVX	FTNMX8770	FTIT8000	NFIN	SPSY	FRFIN	SPTTFS	CXPVX	FTNMX8770	FTIT8000	NFIN
S&P 500 Financials (SPSY)		0.001	0.899	0.049	0.000	0.608	0.000		0.000	0.523	0.018	0.018	0.001	0.000
CAC Financials (FRFIN)	0.249		0.000	0.001	0.385	0.046	0.000	0.000		0.000	0.006	0.005	0.011	0.000
S&P/TSX Canadian Financials (SPTTFS)	0.249	0.010		0.000	0.011	0.002	0.000	0.217	0.002		0.000	0.000	0.002	0.003
DAX Financial Services (CXPVX)	0.763	0.001	0.001		0.027	0.000	0.000	0.000	0.000	0.000		0.001	0.000	0.000
FTSE 350 Financial Services (FTNMX8770)	0.587	0.053	0.067	0.094		0.033	0.000	0.002	0.101	0.002	0.193		0.038	0.000
FTSE Italia All Share Financials (FTIT8000)	0.456	0.473	0.003	0.019	0.844		0.000	0.000	0.000	0.000	0.000	0.000		0.000
Nikkei 500 Other Financial Services (NFIN)	0.000	0.000	0.000	0.001	0.000	0.000		0.036	0.142	0.005	0.445	0.349	0.005	
Granger causality [16 days ~32 days]	SPSY	FRFIN	SPTTFS	CXPVX	FTNMX8770	FTIT8000	NFIN	SPSY	FRFIN	SPTTFS	CXPVX	FTNMX8770	FTIT8000	NFIN
S&P 500 Financials (SPSY)		0.000	0.511	0.006	0.000	0.082	0.000		0.026	0.082	0.286	0.259	0.008	0.000
CAC Financials (FRFIN)	0.713		0.006	0.266	0.003	0.003	0.000	0.000		0.000	0.070	0.546	0.000	0.000
S&P/TSX Canadian Financials (SPTTFS)	0.478	0.002		0.009	0.000	0.002	0.000	0.025	0.043		0.000	0.210	0.001	0.001
DAX Financial Services (CXPVX)	0.004	0.000	0.000		0.036	0.000	0.000	0.000	0.003	0.000		0.000	0.000	0.000
FTSE 350 Financial Services (FTNMX8770)	0.507	0.014	0.229	0.078		0.003	0.000	0.029	0.243	0.061	0.037		0.002	0.000
FTSE Italia All Share Financials (FTIT8000)	0.808	0.057	0.002	0.019	0.002		0.000	0.000	0.000	0.000	0.000	0.006		0.000
Nikkei 500 Other Financial Services (NFIN)	0.211	0.119	0.001	0.051	0.039	0.031		0.446	0.492	0.686	0.903	0.869	0.118	
Granger causality [32 days ~64 days]	SPSY	FRFIN	SPTTFS	CXPVX	FTNMX8770	FTIT8000	NFIN	SPSY	FRFIN	SPTTFS	CXPVX	FTNMX8770	FTIT8000	NFIN
S&P 500 Financials (SPSY)		0.001	0.029	0.000	0.000	0.261	0.000		0.000	0.000	0.041	0.000	0.000	0.000
CAC Financials (FRFIN)	0.559		0.027	0.016	0.328	0.003	0.000	0.001		0.000	0.001	0.253	0.000	0.000
S&P/TSX Canadian Financials (SPTTFS)	0.163	0.034		0.259	0.001	0.018	0.000	0.000	0.011		0.000	0.001	0.000	0.000
DAX Financial Services (CXPVX)	0.263	0.001	0.529		0.000	0.000	0.000	0.000	0.003	0.000		0.001	0.001	0.000
FTSE 350 Financial Services (FTNMX8770)	0.513	0.049	0.006	0.053		0.001	0.000	0.000	0.695	0.000	0.002		0.026	0.000
FTSE Italia All Share Financials (FTIT8000)	0.220	0.026	0.035	0.314	0.479		0.000	0.000	0.000	0.000	0.000	0.002		0.000
Nikkei 500 Other Financial Services (NFIN)	0.007	0.001	0.000	0.000	0.037	0.004		0.002	0.000	0.006	0.066	0.003	0.000	

Notes: Index (row) Granger causes index (column). Only p-values are reported. H0: no Granger causality.
Source: Authors' own findings.

In the appendix, Figure 4.3 reports the 21 possible pairwise combinations with the G7 financial indices. In most of them, the region characterized by a frequency of 16 to 256 days is predominantly dark red, which suggests a VaR ratio greater than 1, that is, stronger contagion between both banking systems. This is particularly true during the pandemic period. Some of the main highlights are the following pairwise: US and France, US and Canada, Canada and France. The highest contagion is found in the Italian and French banking systems, countries severely punished by deaths by COVID-19, while the least contagion, measured by the VaR ratio, is evident between Japan and Germany, countries least affected by the first wave of COVID-19.

Figure 4.2 – Squared VaR Ratio for an equally weighted portfolio of G7 financial sector portfolio, with and without co-movement.



Notes: The cone of influence, region free of edge effects, is shown as the black convex curve. Data from January 01, 2015 to October 16, 2020. Source: Authors' own findings.

4.6 Conclusion and Managerial Implications

We add to the debate on G7 banking contagion during this pandemic based on comparison of risk metrics, dissimilarities, frequency-based Granger causalities and VaR ratio.

Some of our main conclusions suggest an increase in contagion and the effect on risk management, mainly involving the countries most affected by the pandemic. The VaR based analysis suggests that there are banking sectors with more comfortable risk management, as in Germany, while in the US and France, this metric increased by more than 4% in the pandemic. According to the wavelet dissimilarities, the pandemic seems to have intensified this metric of contagion, and the non-significant combinations are associated with the banking sector in Japan, a country little affected by COVID-19. We also may highlight the increase in the predictive relevance of Italian banking cycles during the pandemic. Based on VaR Ratio analysis, we find a stronger banking contagion during the pandemic period, especially considering the height of the pandemic (February and March, 2020). The highest contagion is found in the Italian and French banking systems, countries severely punished by deaths by COVID-19, while the least contagion, measured by the VaR ratio, is evident between Japan and Germany, countries least affected by the first wave of COVID-19.

We believe that the systematic contagion effects present in these markets during this health crisis could not have been necessarily reduced by further banking regulatory measures such as increased capital requirements. However, there is a gain for researchers, and policymakers to consider how does it work the transmission of business cycles between each pair of banking systems or even considering a small group of countries. It seems useful to identify which banking system can act as a leader in the group of synchronized countries. In this context, our main findings are aligned to Matos, da Silva and Oliveira (2019) and they can shed light on this discussion on business cycle synchronization and trade, we also claim that our findings are useful to draw public policies to safeguard financial stability and to analyze the timing of the impact of the pandemic crises in each G7 banking sector.

Furthermore, from a practical point of view, our findings have managerial implications in informing asset managers and banking sector investors decisions alike. For instance, we have evidenced the fact that banking sectors have had much more similar spectrums during the COVID-19 pandemic, indicating increased dynamic correlations in each time horizon, and, thus, less benefits of geographic diversification inside the banking sector during highly stressful moments.

Similar use can be drawn for the Granger causality analysis, that showed a predictability increase, mainly from sectors of countries under high stress, like Italy and the US to the others. This behavior suggests possible suitability of the returns of banking sectors in highly stressed markets as variables in asset pricing models used for asset managers and other finance practitioners.

Finally, the provided pairwise time-frequency maps of VaR ratios, indicates that at the long run, represented by components at frequencies of 16 to 256 days, there is evidence of historically high linkages between banking sectors, one that is increased considerably during this pandemic. Thus, the geographic diversification provided in a banking portfolio of G7 countries is shown to be more important to protect for the short run minded investor. Another use of the VaR ratios maps is to indicate the less connected pairwise of banking sectors in a time-frequency manner, hinting best candidates for a portfolio formation given the time horizon interest of the investor.

4.7 Suggestion for Future Research

The present work has been focused on the linkages between returns, but could well have used metrics of risks, as volatilities or VaR itself, as the variables of interest. This approach could yield some new perspectives, as discussed in Diebold and Yilmaz (2019). However, we have not added other metrics of risk as the variables of interest in this work because of the space needed. Thus, we understand this would be a natural extension to be addressed in future research.

We also understand that there are other groups of countries to be addressed, to which the framework here employed could bring some new results. Specifically, an interesting extension of this work could be obtained focusing on relevant emerging markets, for instance, the BRICS.

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Appendix

Figure 4.3 – Ratio between the VaR of an equally weighted portfolio taking into account each pairwise of financial sector indices with and without co-movement.

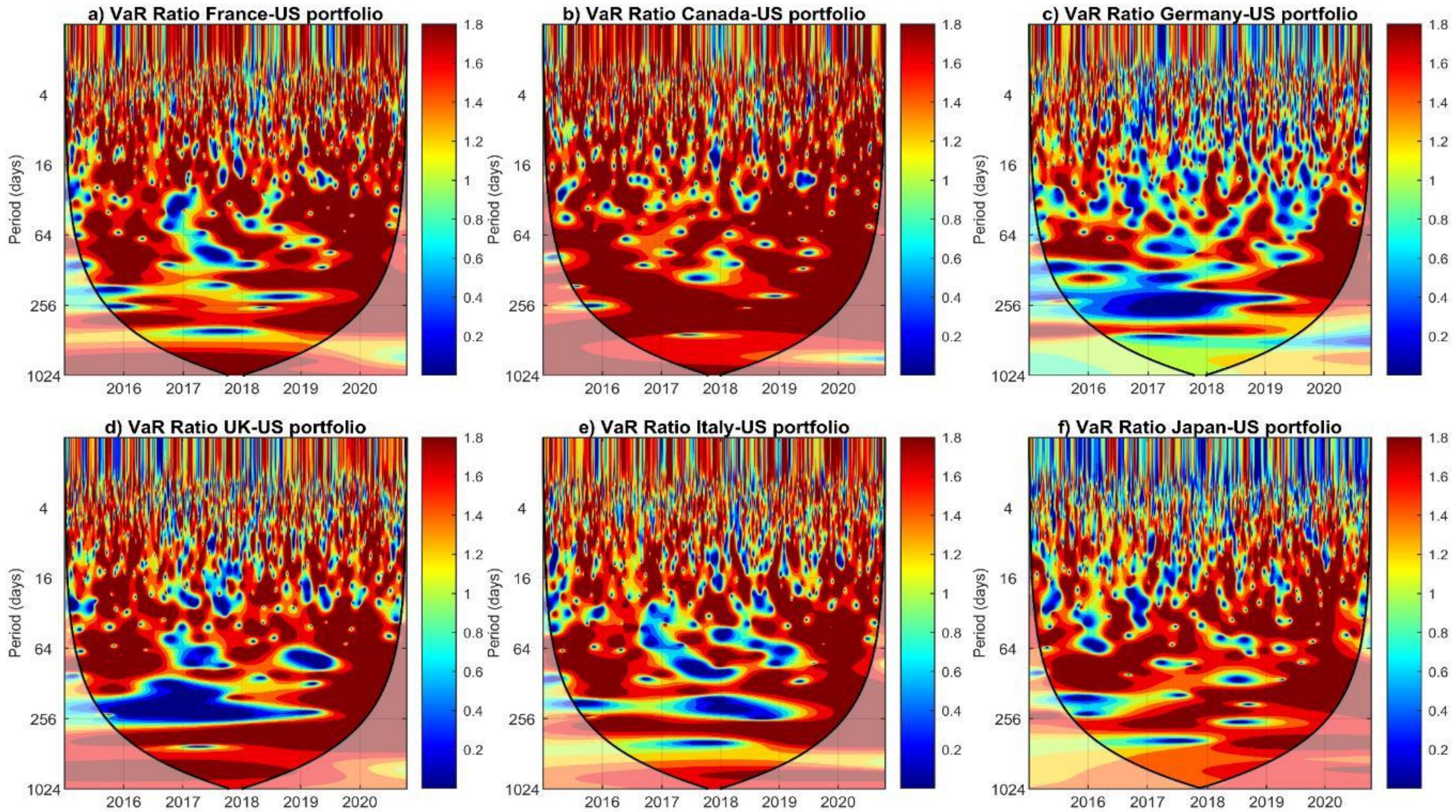

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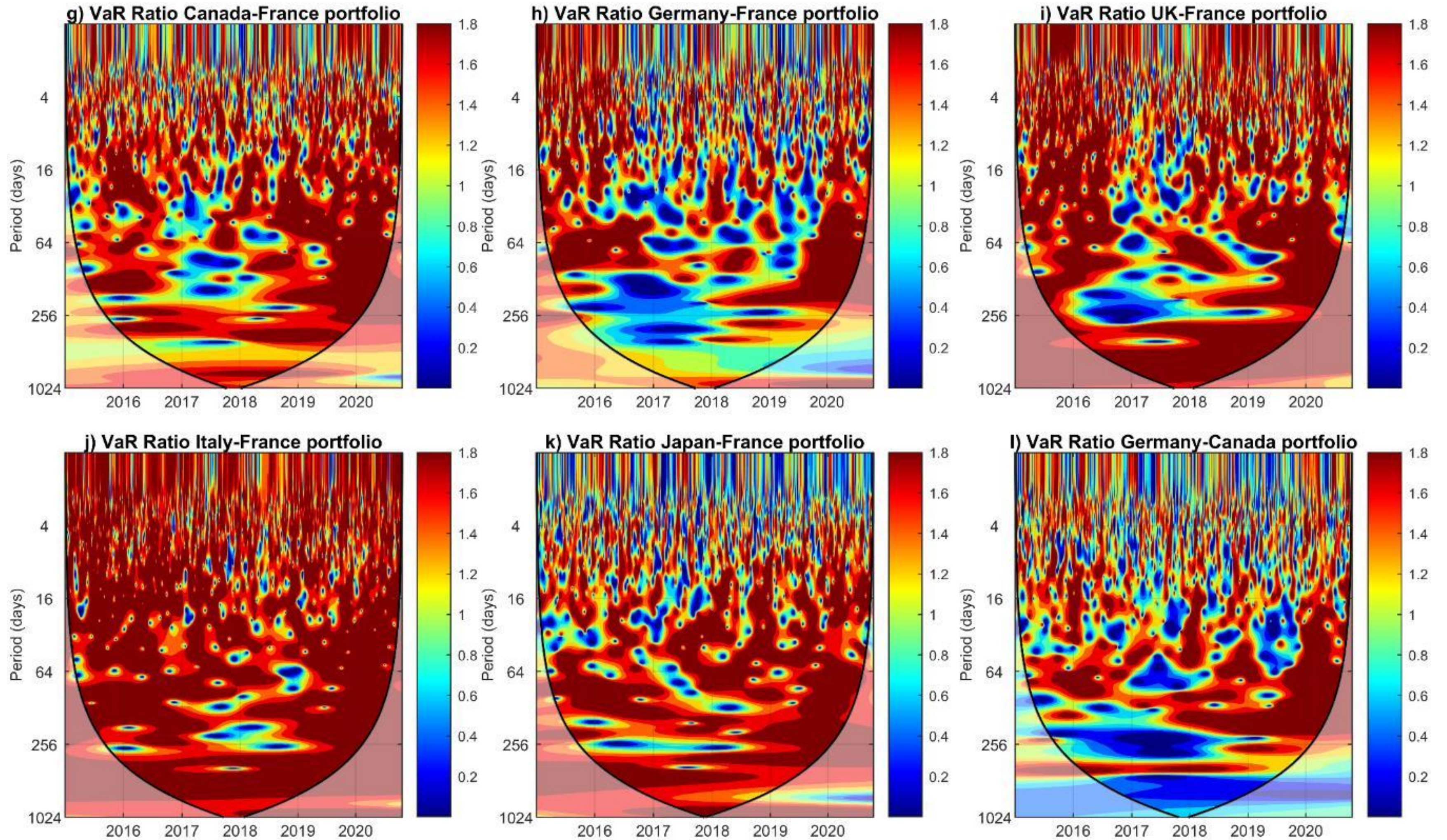
Figure 4.3 – Ratio between the VaR of an equally weighted portfolio taking into account each pairwise of financial sector indices with and without co-movement.



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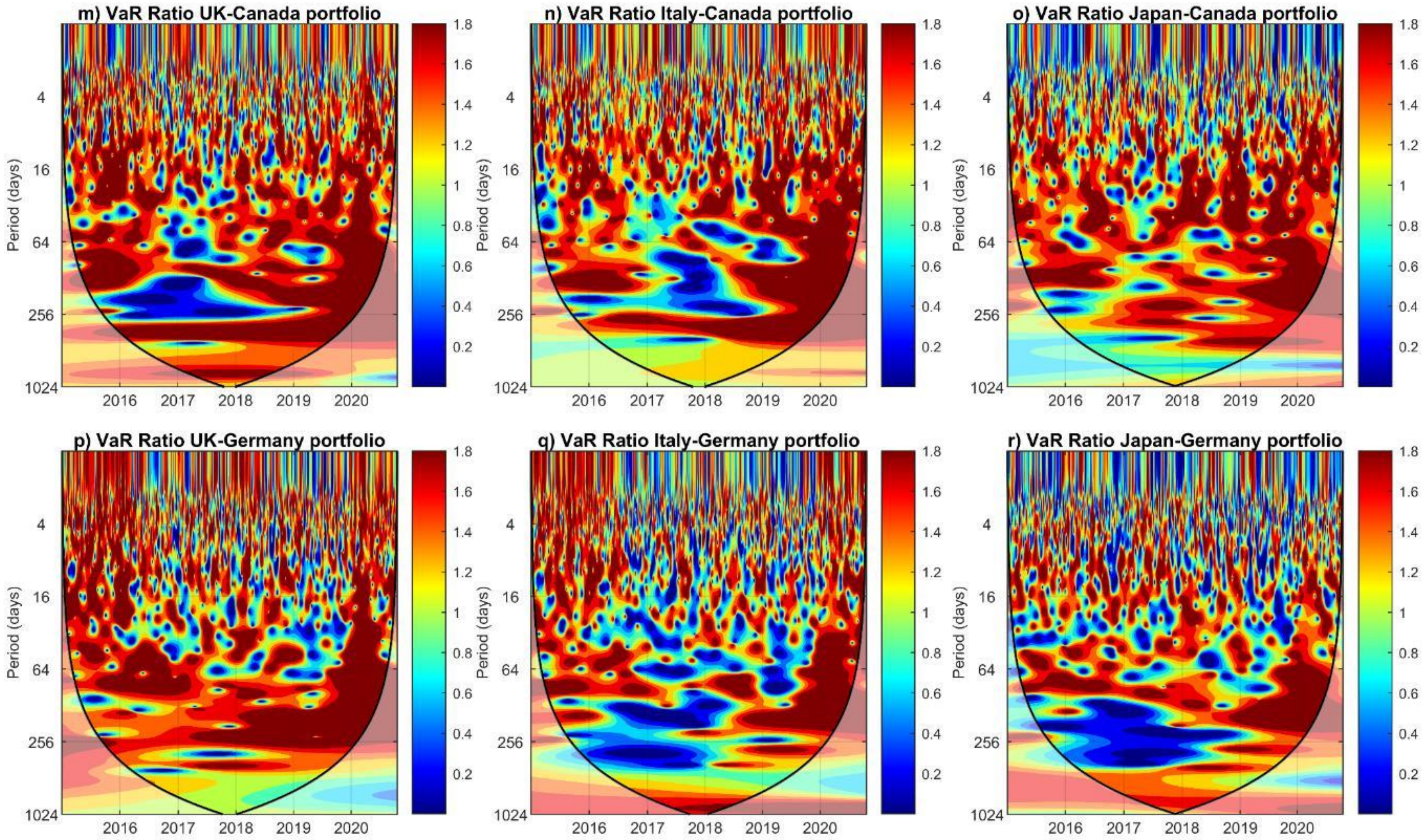

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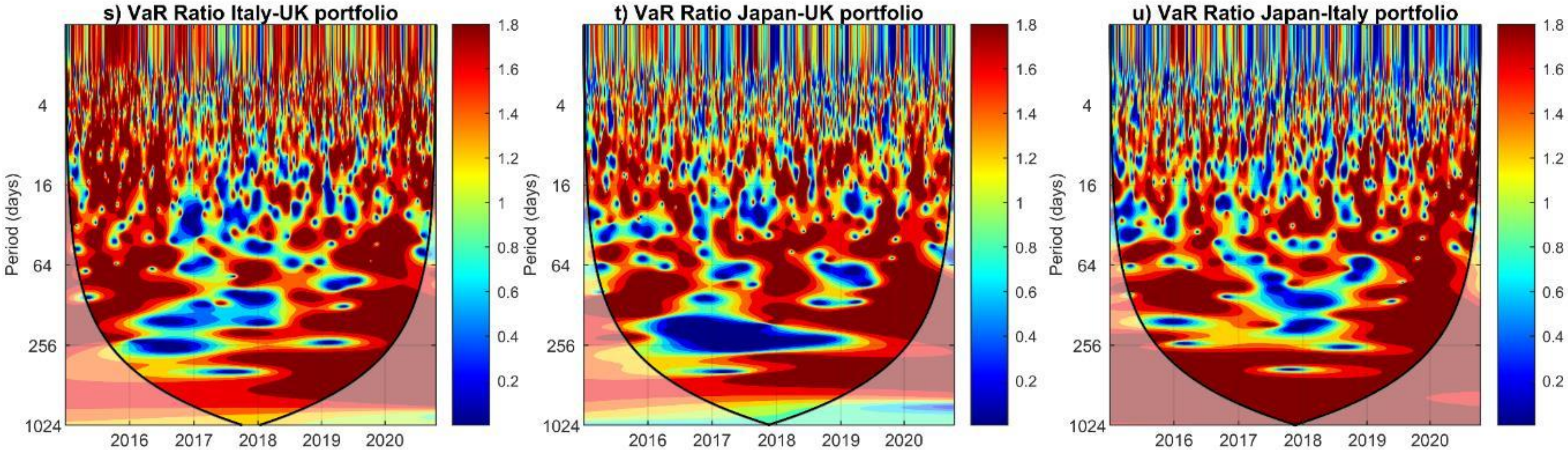
Figure 4.3 – Ratio between the VaR of an equally weighted portfolio taking into account each pairwise of financial sector indices with and without co-movement.



Notes: The cone of influence, region free of edge effects, is shown as the black convex curve. Data from January 01, 2015 to October 16, 2020. Source: Authors' own findings.

5 ON THE RELATIONSHIP BETWEEN COVID-19 AND G7 BANKING CO-MOVEMENTS

5.1 Introduction

The banking system is one of the most vulnerable to financial contagion, mainly during periods of instability. Specifically about the last global crisis of 2007, Dungey and Gajurel (2015) address this contagion involving more than 50 economies through the channels systematic, idiosyncratic, and also volatility, and concerning its effects, Laeven and Valencia (2013) estimate a loss of 30% of GDP due to this banking crisis.

After more than a decade, another global crisis: a pandemic that has already killed more than one million two hundred thousand people worldwide by the end of October 2020. According to Goodell (2020), the main concerns with this pandemic arise from rising costs for health systems, loss of job productivity, social distance that disrupts economic activity, depressed tourism and impacts on foreign direct investment. With regards the financial markets, Zhang, Hu and Ji (2020) highlight the change of pattern in the global stock market spillovers after the COVID-19 outbreak.

In line with this previous literature on the short run linkages among financial markets during crisis, we recognize the relevance of the frequency dependent nature of the international financial co-movements reported in Fidrmuc, Ikeda and Iwatsubo (2011), and we use partial wavelet coherency to measure the cross-correlation between pairwise of G7 financial sector indices allowing for varying time and frequency. Since we use COVID-19 cases and deaths as instruments, we can conclude whether part of their interdependence was due to pandemic. To ensure robustness, we use a statistical correlation contagion test.

The letter is organized as follows. Section 5.2 presents the methodology. Section 5.3 describes the results. Section 5.4 concludes.

5.2 Methodology

Wavelet analysis provide a decomposition of time series in the time-frequency (scale) space. The continuous wavelet transform (CWT) of $x(t) \in L^2(\mathbb{R})$ with respect to the Morlet wavelet ψ is given by:

$$W_x(\tau, s) = \int_{-\infty}^{\infty} x(t) \frac{1}{\sqrt{|s|}} \psi^* \left(\frac{t-\tau}{s}\right) dt \tag{5.1}$$

where, * represent complex conjugation, and (τ, s) localize the wavelet transform in the time-frequency space.

Given a pair of series, $x(t)$ and y(t), we define the cross-wavelet transform (XWT):

$$W_{xy}(\tau, s) = W_x(\tau, s)\, W_y^*(\tau, s) \tag{5.2}$$

Normalizing the XWT by the individual spectra we obtain the wavelet coherency (WC):

$$R_{xy}(\tau, s) = \frac{\left|S\left(W_{xy}(\tau,s)\right)\right|}{\left[S(|W_x(\tau,s)\,|^2)S(|W_y(\tau,s)\,|^2)\right]^{1/2}} \tag{5.3}$$

where S is a smoothing operator. The WC measures the cross-correlation between x_1 and x_2 as a function of time and frequency. Given x_1, x_2 and x_3, we define the partial wavelet coherence (PWC) of x_1 and x_2 controlling for x_3 as:

$$r_{1\,2.3}(\tau, s) = \frac{R_{12}(\tau,s)}{\left[(1-R_{12}(\tau,s)^2)(1-R_{23}(\tau,s)^2)\right]^{1/2}} \tag{5.4}$$

Whether after controlling for the instruments, the PWC decreases in some region of the time-frequency space, we conclude that part of their interdependence was due to that third variable (Aguiar-Conraria and Soares, 2014).

Here, we assume that that WC among financial indices work as a proxy of banking contagion, and we use PWC to determine if COVID-19 numbers can explain the contagion among banking systems.

As a robustness, we use the correlation contagion test framework proposed by Forbes and Rigobon (2002) and Fry et al. (2010). To test contagion from a source X to a recipient Y, we divide the return series in pre-crisis and crisis periods, with lengths of N_{pre} and N_c respectively. We then define the adjusted correlation:

$$v_c = \frac{\rho_c}{\sqrt{1+\delta(1-{\rho_c}^2)}} \tag{5.5}$$

where ρ_c is the correlation during crisis, $\delta = \left(Var_{X,c} - Var_{X,pre}\right)/Var_{X,c}$ and $Var_{X,c}$ and $Var_{X,pre}$ represent the country X returns variance during crisis and pre-crisis respectively. Fry et al (2010) define the FR statistic:

$$FR(X \to Y) = \left(\frac{v_c-\rho_{pre}}{\sqrt{Var(v_c-\rho_{pre})}}\right)^2 \tag{5.6}$$

where ρ_{pre} is the correlation coefficient during pre-crisis. Fry et al (2010) show that under the null hypotheses of no contagion, FR is asymptotically distributed as $FR(X \to Y) \overset{d}{\to} \chi_1^2$. To compute FR, we employ two days moving average of returns to eliminate the non-synchronous trading effect. We also follow Wang et al. (2017), by using a bivariate VAR model with five lags to filter serial autocorrelation in data.

5.3 Data and empirical results

We use daily returns on G7 financial sector indices (FSI): S&P 500 Financials (US), CAC Financials (France), S&P/TSX Canadian Financials (Canada), DAX Financial Services (Germany), FTSE 350 Financial Services (UK), FTSE Italia All Share Financials (Italy), and Nikkei 500 Other Financial Services (Japan). We use returns in terms of local investors' currency, following Mink (2015). The data source is investing.com.

Over the period from January 01, 2015, to December 31, 2019 – characterized by a period without crisis by NBER –, only the Italian banking sector recorded a cumulative loss of 13.2%, while other banking indices showed cumulative gains, ranging from 9.7% in Japan to 123.1% in Germany.

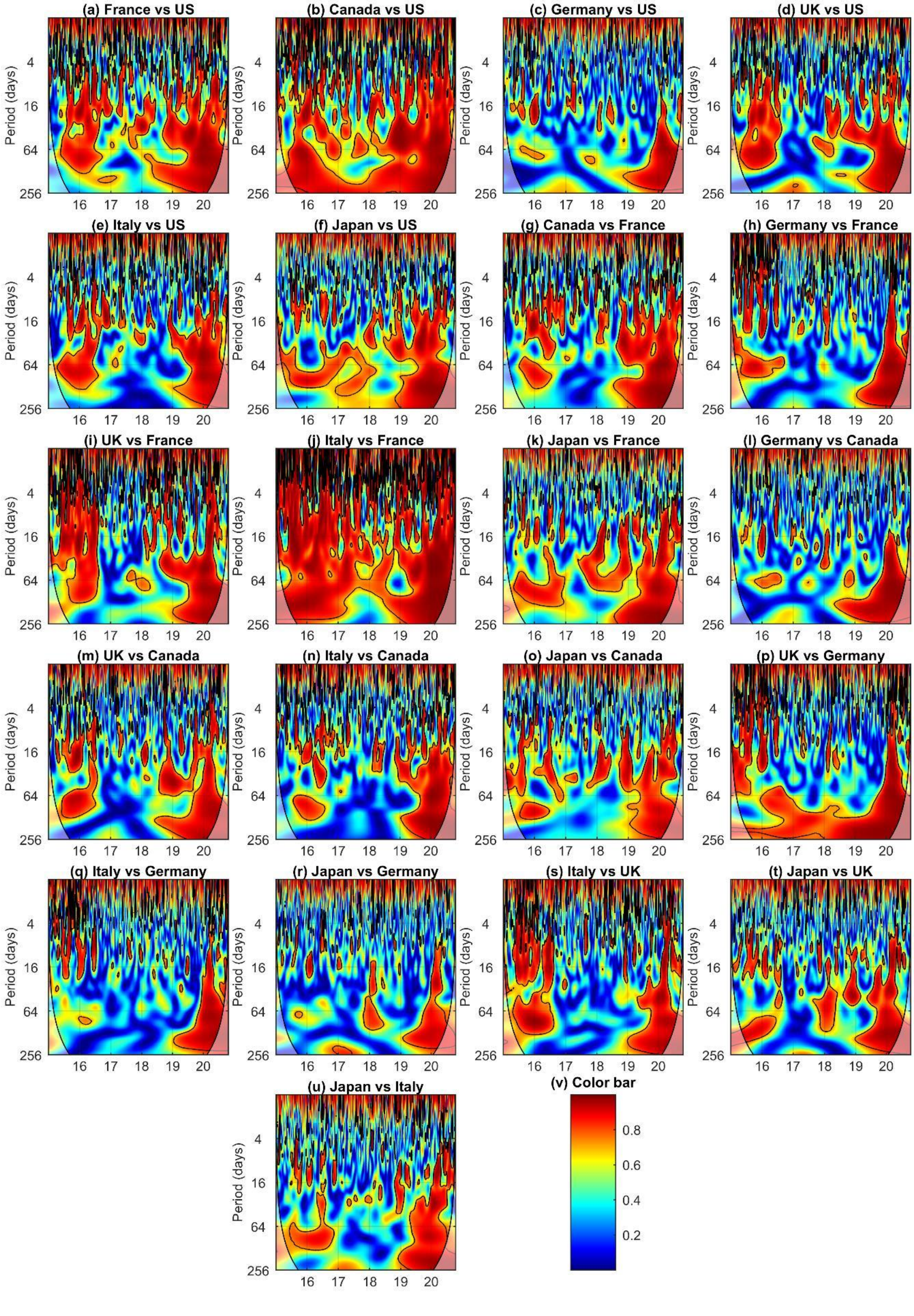
We assume the crisis begins on January 01, 2020 – one day after Wuhan's (China) pneumonia cluster has been reported to WHO. The cumulative return in the year 2020, however, suggests a pattern with very sharp cumulative declines from the second half of February, again with divergence from the German banking sector, from the second half of March 2020. DAX Financial Services is the only one that registered a cumulative return from January 1, 2020, to October 16, 2020, exceeding 5%.

Regarding the instruments, we use WTI logged oil prices provided by US Energy Information Administration and also daily log growth of 7-days moving average of new COVID-19 cases and deaths from Johns Hopkins University (JHU).

According to Figure 5.1, throughout the period from 2015 to 2020, there is no significant coherence at the highest frequencies, 1 ~ 4 days, with specific exceptions, as in the relationship between Canada and the US or between European countries.

However, observing the lowest frequencies, 16 ~ 264 days, there is banking contagion based on strong coherence between all pairs of banking systems, and this contagion is intensified during the pandemic period. Comparing the average value of coherence across frequencies across all 21 pairwise, there is an increase of 20% during the pandemic, compared to the period before the current crisis. The relationship between Italian and German banks is interesting: there is only a sign of contagion during the pandemic, with a 34% increase in coherence.

Figure 5.1 – Wavelet Coherence among international FSI.



Notes: The black contours designate 5% significance levels derived from Monte Carlo simulations. The coherence power scale is provided in (v). Data from January 01, 2015, to October 16, 2020.

Figure 5.2 – (Partial) Coherence between G7 FSI, left (controling for COVID-19 cases and deaths, right).

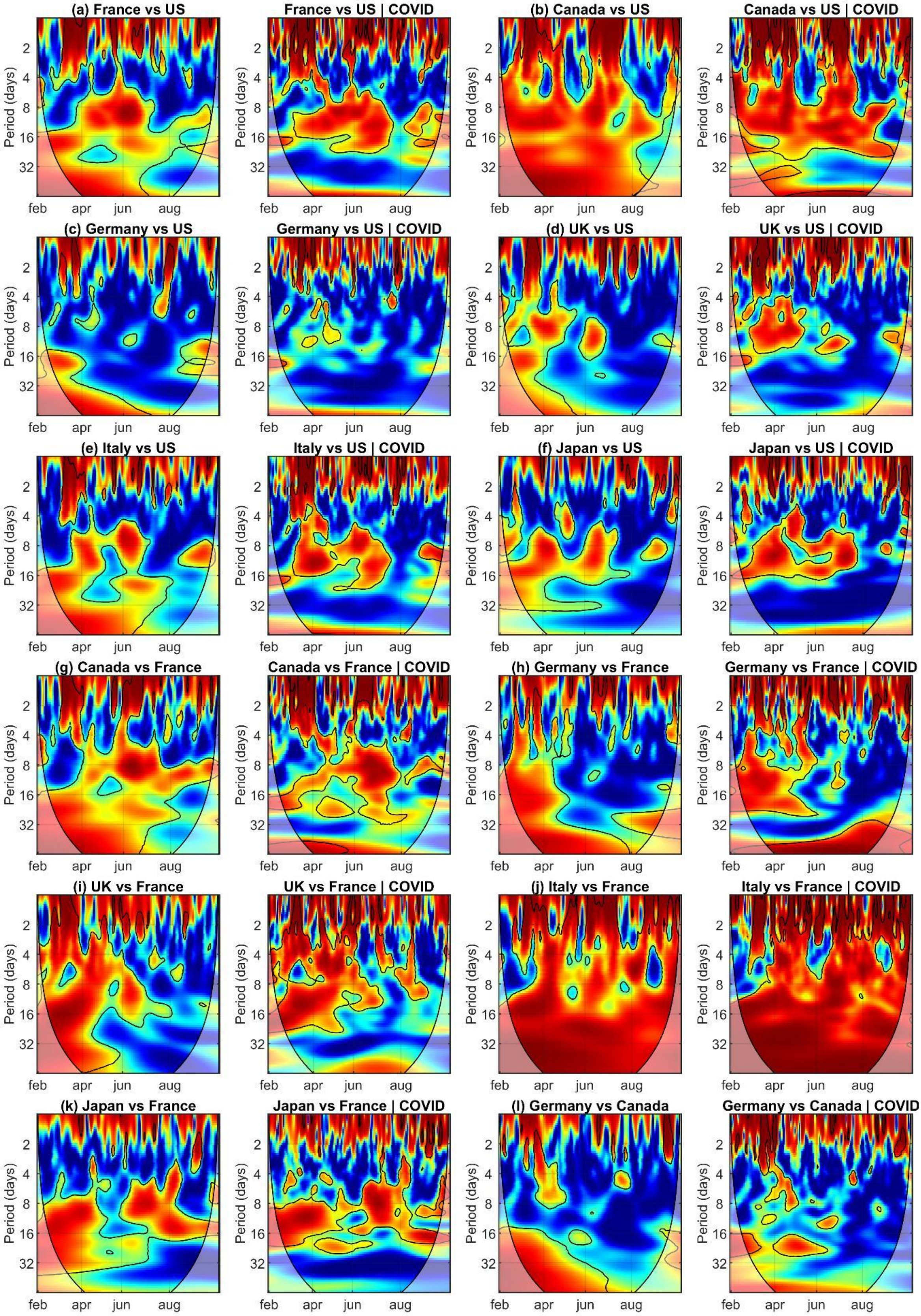


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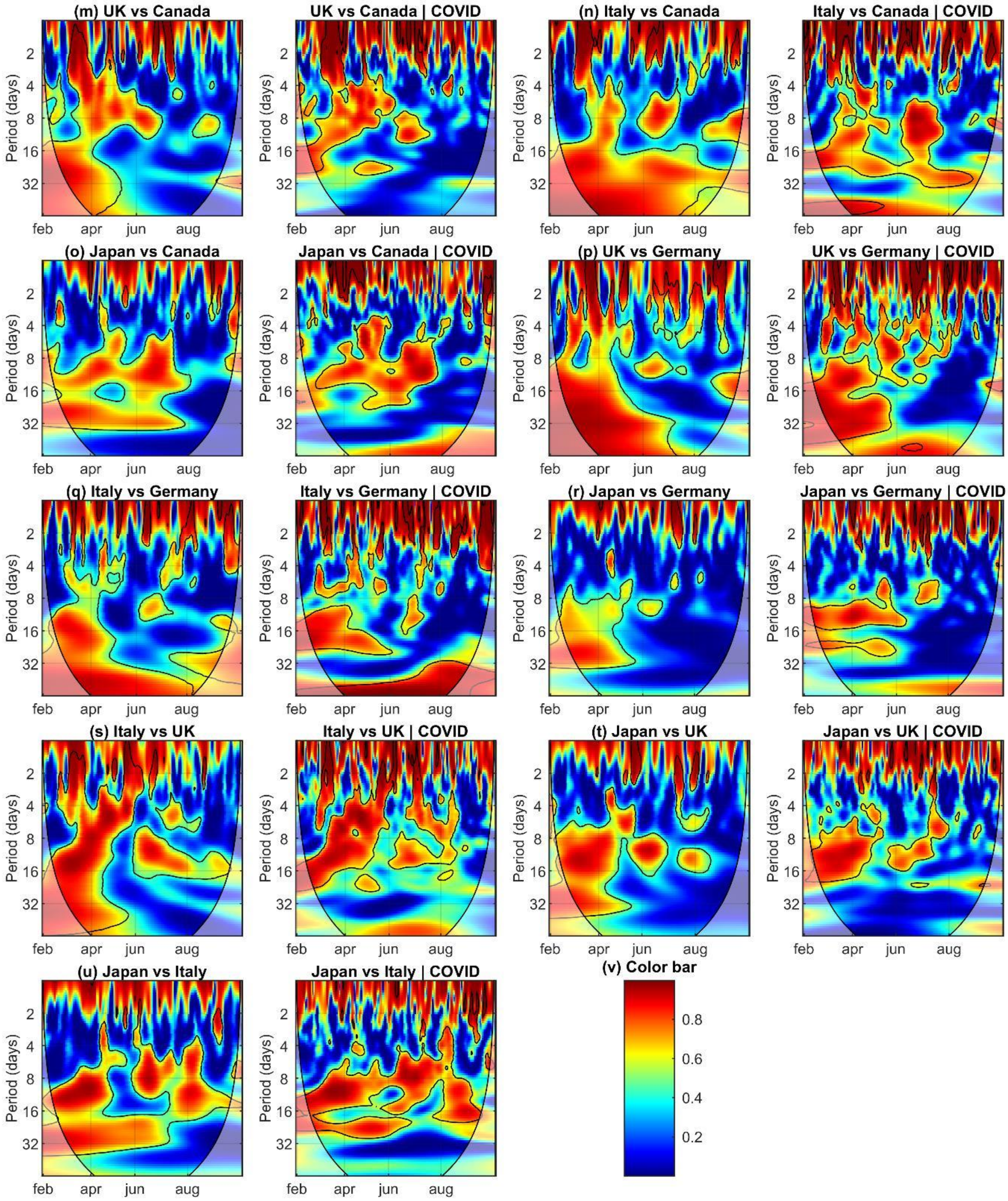
Figure 5.2 – (Partial) Coherence between G7 FSI, left (controling for COVID-19 cases and deaths, right).

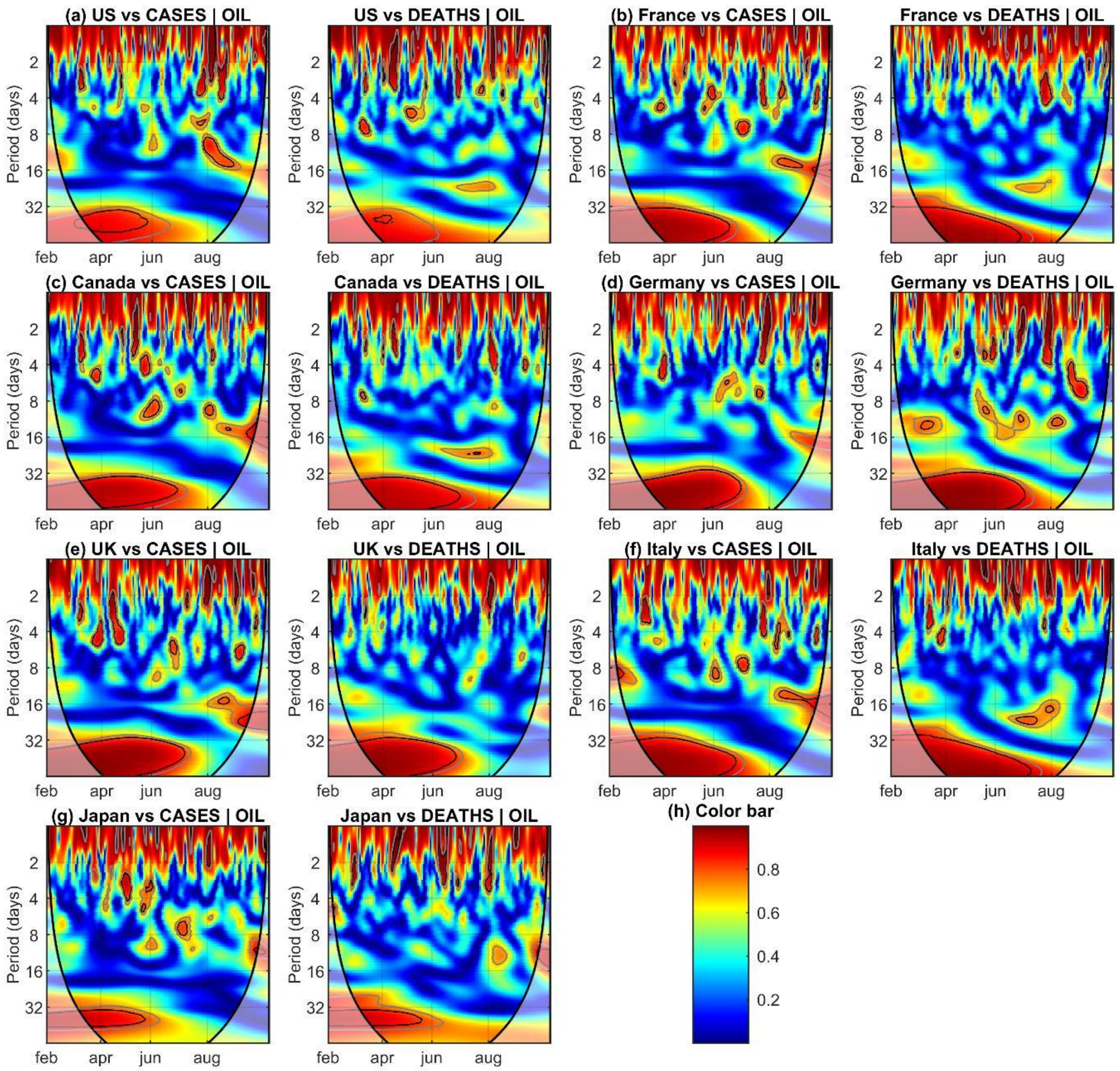


Notes: The black contours designate 5% significance levels derived from Monte Carlo simulations. The (partial) coherence power scale is provided in (v). Data from January 22 to October 16, 2020.

In Figure 5.2, we report each G7 pairwise during the pandemic with and without COVID-19 case and death data in both countries.

We find a strong reduction in the size of significant partial coherency area after controlling for COVID-19 for all 21 G7 pairwise. In average, this reduction was of 36.5% across all frequencies during 2020. Germany-US (Italy-France) have showed the highest (lowest) reduction with 76.3% (3.6%) variation. This reduction was particularly strong at the 16-64 days scales, with an average reduction of 56.8%. It suggests that COVID19 numbers are relevant to better understand G7 banking systems co-movement.

Figure 5.3 – Partial coherence between G7 FSI and COVID-19 cases (left) and deaths (right) controlling for oil prices.



Notes: The black (grey) contours designate 5% (10%) significance levels derived from Monte Carlo simulations. The (partial) coherence power scale is provided in (h). Data from January 22 to October 16, 2020.

Aiming to avoid cofounding with crude oil price-war between Saudi Arabia and Russia, we propose as our first robustness check examining the influence of COVID-19 world cases and deaths over FSI controlling for oil prices (Figure 5.3). We find high and significant area in the PWC at 32-64 days scale from February to June in all cases. This result supports COVID-19 outbreak as a key driver of contagion among the FSI at long cycles frequencies.

Table 5.1 reports the statistical correlation contagion test performed.

In all 21 pairwise, the correlation increases in the pandemic, compared to the pre-crisis period. On average, the correlation during the crisis is 50% higher than in the pre-crisis period. Based on FR statistic test, we reject the null hypothesis of no contagion (at 10%) in 30, among 42 pairwise tests performed. We highlight US-France, US-Canada, France-Canada, France-UK, Canada-Italy, Canada-Japan, Italy-Japan, since these pairwise show bidirectional contagion. The banking system in Japan has a greater capacity for contagion, while in Germany, the banking system seems to be the least contagious. Both countries were relatively unaffected by COVID-19 deaths.

Table 5.1 – Test for FSI contagion during COVID-19 crisis

Correlations [a]	SPSY	FRFIN	SPTTFS	CXPVX	FTNMX8770	FTIT8000	NFIN
S&P 500 Financials (SPSY)		0.58	0.72	0.29	0.50	0.50	0.25
CAC Financials (FRFIN)	0.79		0.55	0.52	0.73	0.86	0.28
S&P/TSX Canadian Financials (SPTTFS)	0.92	0.75		0.34	0.50	0.49	0.24
DAX Financial Services (CXPVX)	0.61	0.71	0.59		0.57	0.40	0.20
FTSE 350 Financial Services (FTNMX8770)	0.77	0.85	0.79	0.80		0.62	0.30
FTSE Italia All Share Financials (FTIT8000)	0.70	0.92	0.70	0.67	0.80		0.18
Nikkei 500 Other Financial Services (NFIN)	0.48	0.54	0.50	0.36	0.51	0.49	
FR statistic [b]	SPSY	FRFIN	SPTTFS	CXPVX	FTNMX8770	FTIT8000	NFIN
S&P 500 Financials (SPSY)		18.6***	8.06***	0.32	7.70***	15.9***	1.84
CAC Financials (FRFIN)	12.5***		12.3***	14.9***	38.0***	44.9***	0.00
S&P/TSX Canadian Financials (SPTTFS)	52.8***	69.7***		19.7***	28.5***	44.6***	4.95**
DAX Financial Services (CXPVX)	4.20**	0.72	1.52		0.95	2.57	0.20
FTSE 350 Financial Services (FTNMX8770)	0.09	13.1***	2.86*	0.02		3.00*	0.02
FTSE Italia All Share Financials (FTIT8000)	3.74*	0.00	5.70**	12.6***	5.48**		15.8***
Nikkei 500 Other Financial Services (NFIN)	5.68**	12.6***	7.96***	2.80*	6.31**	18.3***	

Notes: Data from January 01, 2015, to December 31, 2019 (upper triangle) and from January 01, 2020, to October 16, 2020 (lower triangle). To measure $FR(X \rightarrow Y)$ statistic, we consider index X (column) and index Y (row). * p-value < 0.10, ** p-value < 0.05 and *** p-value < 0.01.

5.4 Conclusion

We add to the discussion on monitoring G7 banking contagion during this current and atypical global crisis due to the pandemic. Some of our main conclusions suggest a robust increase in contagion, mainly involving the countries most affected by the pandemic. We may highlight the difference of the behavior of co-movements involving Italian banking cycles, vis-à-vis banking cycles in Japan, for instance. Our findings are useful to anticipate and reduce potential financial and economic impacts arising from the banking crisis. We claim that this letter is also useful to draw public policies to safeguard financial stability and to analyze the timing of the impact of the pandemic crisis in each G7 banking sector.

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6 SECTORAL CONNECTEDNESS: NEW EVIDENCE FROM US STOCK MARKET DURING COVID-19 PANDEMICS

6.1 Introduction

The COVID-19 appeared in Wuhan, China in December 2019. Initially thought as a pneumonia cluster, it rapidly developed to receive the WHO pandemic status on March 11, 2020. By the end of 2020, there have been more than 83.5 million cases, with 1.8 million deaths in 192 affected countries. In the real economy, the consequences were likewise devastating. According to Goodell (2020), concerns arise from health systems costs, job productivity loss, disrupted economic activity, tourism, and foreign direct investment.

As expected, the spillovers to worldwide financial markets have been considerable. For instance, Baker et al. (2020), comparing the current crisis with other pandemic periods, argue that no disease outbreak, including the Spanish Flu, has impacted the US stock market as forcefully as COVID-19. Ashraf (2020) suggests that stock markets quickly reacted to COVID-19 and that this response depends on the outbreak stage. In this sense, Corbet, Larkin, and Lucey (2020) show that, at earlier stages of COVID-19, Chinese financial markets acted as the epicenter of financial contagion, and Ali et al. (2020) find that while the earlier epicenter China has stabilized, global markets went into freefall.

Still in this literature on pandemic financial impacts, but with an emphasis on volatility, according to Haroon and Rizvi (2020), the COVID-19 outbreak resulted in unprecedented news coverage and the ensuing uncertainty in financial markets lead to heightened volatility. Lyócsa et al. (2020) find that COVID-19 related Google search volume predicts price variations. Sharif et al. (2020) report unprecedented impact of COVID-19 and oil price shocks on stock volatility, while Zhang et al. (2020) show substantial increase in volatility and clearly different patterns of stock markets linkages before and after the pandemic.

Considering its unprecedented nature, COVID-19 pandemic may entail important qualitative changes in the dynamics of financial markets. Therefore, extensive re-examinations of previous findings are occurring. Indeed, it is possible that COVID-19 will alter entire research streams (Yarovaya et al., 2020).

A particularly hot topic during COVID-19 re-examinations has been financial connectedness[9]. For instance, Amar et at. (2021), examine the spillovers and co-movements

[9] Financial connectedness has been measured using a variety of approaches as dynamic conditional correlation (DCC) of Engle (2002), CoVaR of Adrian and Brunnermeier (2016) and concepts of network topology, being related to terms as spillovers and contagion. In this work we use Diebold and Yilmaz (2009, 2012, 2014) measures.

among commodity and stock prices major oil-producing and consuming countries. Corbet et al. (2021) study volatility spillovers from Chinese financial markets upon a number of traditional financial assets. Rizwan et al. (2020) analyze systemic risk of banking sectors across the globe. Hernandez et al. (2020) examine the network spillovers, portfolio allocation characteristics and diversification potential of bank returns from developed and emerging America. Akhtaruzzaman et al. (2021) study how financial contagion occurs through financial and nonfinancial firms between China and G7 countries during the COVID-19 period. Matos et al. (2021) study sectoral contagion in the US during COVID-19 besides the impact of the pandemic over the S&P 500. Corbet, Goodell, and Günay (2020) examine co-movement and spillovers of oil and renewable firms under the event of negative WTI prices occurred during COVID-19. Fasanya et al. (2020) consider the connectedness between COVID-19 and global foreign exchange markets. Karkowska and Urjasz (2021) examine the connectedness structures of sovereign bond markets in central and eastern Europe.

This interest is justifiable once financial connectedness is of great practical use for a broad audience given its importance to various aspects of risk. Particularly during crisis and turbulent periods as COVID-19 pandemic, various economic agents, including investors and policymakers, can make use of the size and direction of the net spillovers for enhancing portfolio decisions and the formulations of policy to restore and safeguard financial stability (Bouri et al., 2021). For the academic community, studying connectedness at this very moment should be important to better grasp the range of implications of highly stressing moments over the financial markets.

Sectoral connectedness is arguably of similar importance for a large portion of investors and asset managers that deal with national portfolios and for virtually all policy makers. It can also provide different insights to the academic community, once it could signal some internal dynamic that is specific of a given country and would not be completely unveiled using aggregate data. Nevertheless, sectoral connectedness has not received nearly as much attention as studies focusing on aggregated markets, as discussed in Mensi et al. (2020).

More related to our study, regarding sectoral connectedness in the US, Baruník et al (2016) examine asymmetries in volatility spillovers using most liquid stock in seven sectors. They find that spillovers are transmitted at different magnitudes that sizably change over time in different sectors and a substantial connectedness increase during the GFC. Also, Mensi et al. (2020) study volatility connectedness among ten US sectors from 2012 to 2018. They find time-

Refer to Diebold and Yilmaz (2015) for a detailed comparison of concurrent approaches.

varying spillovers among US sectors which is intensified during economic, energy and geopolitical events.

In this study, we contribute to the literature by examining for the first time how the network of sectoral indices in the US is affected by such an unprecedented turmoil as the COVID-19 pandemic. More specifically, to our knowledge, we are the first to examine the sectoral connectedness among eleven US sectors covering an entire year of COVID-19 pandemic and using Dielbold and Yilmaz (2009, 2012, 2014) methodology. We use daily volatility data from January 01, 2013, to December 31, 2020, providing both a relatively tranquil pre-COVID-19 baseline for comparative analysis and an entire year of COVID-19 pandemic data.

The main aim is to examine possible quantitative (levels) and qualitative (roles/directions) changes occurred during COVID-19 as well as to observe stylized facts regarding specific sectors behavior under pandemics context.

Among several results, we find extraordinary increase in total connectedness among US sectoral indices volatility during COVID-19. Furthermore, in the pairwise connections between the sectors, both intensity and directions have presented some relevant changes. Also, we find particularly relevant behavior of specific sectors like Financials and Energy. Our findings encounter practical use for asset managers and policy makers alike.

The remainder of this study is organized as follows. Section 6.2 delineates the methodology. Section 6.3 shows the data and a preliminary analysis. Section 6.4 presents the empirical results. Section 6.5 contains robustness checks, while Section 6.6 concludes.

6.2 Methodology

The core methodology used in this study is the connectedness indices of Diebold and Yilmaz (2009, 2012, 2014). It enables us to fulfil our objectives - highlight both quantitative (levels) as qualitative (roles/directions) changes in sectoral connectedness occurred, as well as any unusual behavior of specific sectors - by means of static and dynamics analysis of the proper connectedness indices.

As discussed in Corbet, Goodell, and Günay (2020), this model has a number of advantages, namely, it allows bilateral spillovers unlike the SAMEM model of Otranto (2015), it allows displaying the strength of spillovers and enable proper comparisons among alternative model configurations and variable sets. Regarding concurrent correlation-based methods, as Wavelet analysis and the multivariate GARCH models, we believe the chosen methodology is advantageous because it is able to infer direction of spillovers for a large number of simultaneously interacting variables in a clear and compact manner.

Consider a covariance stationary N-variable VAR(p), $x_t = \sum_{i=1}^{p} \Phi_i \, x_{t-i} + \sum_{j=1}^{Nsb} D_{jt} I_N \gamma_j + \varepsilon_t$, with MA representation $x_t = \sum_{i=0}^{\infty} \mathrm{A}_i \, \varepsilon_{t-i}$, where $\varepsilon \sim (0, \Sigma)$ is a vector of *i.i.d.* disturbances with covariance matrix Σ, I_N is the identity matrix, and D_j are dummy variables that account for structural breaks.

Using the generalized[10] VAR (GVAR) framework of Koop, Pesaran, and Potter (1996) and Pesaran and Shin (1998), the H-step-ahead error variance in forecasting x_i that are due to shocks in x_j, $i, j = 1,2, \dots, N$ is computed as:

$$\theta_{ij}^{g}(H) = \frac{\sigma_{jj} \sum_{h=0}^{H-1} \left(e_i^{'} A_h \Sigma e_j\right)^2}{\sum_{h=0}^{H-1} \left(e_i^{'} A_h \Sigma A_h^{'} e_i\right)} \tag{6.1}$$

where σ_{jj} is the standard deviation of the error for the j[th] equation, and e_i is the selection vector, with one as the i[th] element and zeros otherwise. As the shocks in the GVAR framework are not orthogonal, one needs to normalize (1) in the following manner to obtain the generalized forecast error variance shares:

$$\tilde{\theta}_{ij}^{g}(H) = \frac{\theta_{ij}^{g}(H)}{\sum_{j=1}^{N} \theta_{ij}^{g}(H)} \tag{6.2}$$

The essential idea of Diebold and Yilmaz (2009, 2012, 2014) is to construct a connectedness table, such as Table 6.1 (Zhang, 2017). From this table, a series of connectedness indices are formed, as follows.

Table 6.1 – Connectedness table based on variance decomposition.

	$\boldsymbol{x_1}$	$\boldsymbol{x_2}$	$\cdots$	$\boldsymbol{x_N}$	From others
$\boldsymbol{x_1}$	$\boldsymbol{\tilde{\theta}_{11}^{g}(H)}$	$\boldsymbol{\tilde{\theta}_{12}^{g}(H)}$	$\cdots$	$\tilde{\theta}_{1N}^{g}(H)$	$\sum_{j=1}^{N} \tilde{\theta}_{1j}^{g}(H), j \neq 1$
$\boldsymbol{x_2}$	$\boldsymbol{\tilde{\theta}_{21}^{g}(H)}$	$\boldsymbol{\tilde{\theta}_{22}^{g}(H)}$	$\cdots$	$\tilde{\theta}_{2N}^{g}(H)$	$\sum_{j=1}^{N} \tilde{\theta}_{2j}^{g}(H), j \neq 2$
$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$	$\vdots$
$\boldsymbol{x_N}$	$\boldsymbol{\tilde{\theta}_{N1}^{g}(H)}$	$\boldsymbol{\tilde{\theta}_{N2}^{g}(H)}$	$\cdots$	$\tilde{\theta}_{NN}^{g}(H)$	$\sum_{j=1}^{N} \tilde{\theta}_{Nj}^{g}(H), j \neq N$
To others	$\boldsymbol{\sum_{j=1}^{K} \tilde{\theta}_{j1}^{g}(H)}$, $\boldsymbol{j \neq 1}$	$\boldsymbol{\sum_{j=1}^{K} \tilde{\theta}_{j2}^{g}(H)}$, $\boldsymbol{j \neq 2}$	$\cdots$	$\sum_{j=1}^{N} \tilde{\theta}_{jN}^{g}(H)$, $j \neq N$	$\frac{1}{N} \sum_{i,j=1}^{N} \tilde{\theta}_{ij}^{g}(H)$, $j \neq i$

[10] This approach makes the forecast error variance decomposition invariant to the ordering of variables in the VAR and is used in this study.

The total connectedness index:

$$S^g(H) = \frac{\sum_{\substack{i,j=1 \\ i\neq j}}^{N} \tilde{\theta}_{ij}^{g}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^{g}(H)} \cdot 100 = \frac{\sum_{\substack{i,j=1 \\ i\neq j}}^{N} \tilde{\theta}_{ij}^{g}(H)}{N} \cdot 100 \tag{6.3}$$

The directional connectedness from ("from") all other markets j to market i:

$$S_{i\cdot}^g(H) = \frac{\sum_{\substack{j=1 \\ j\neq i}}^{N} \tilde{\theta}_{ij}^{g}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^{g}(H)} \cdot 100 = \frac{\sum_{\substack{j=1 \\ j\neq i}}^{N} \tilde{\theta}_{ij}^{g}(H)}{N} \cdot 100 \tag{6.4}$$

The directional connectedness to ("to") all other markets j from market i:

$$S_{\cdot i}^g(H) = \frac{\sum_{\substack{j=1 \\ j\neq i}}^{N} \tilde{\theta}_{ji}^{g}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^{g}(H)} \cdot 100 = \frac{\sum_{\substack{j=1 \\ j\neq i}}^{N} \tilde{\theta}_{ji}^{g}(H)}{N} \cdot 100 \tag{6.5}$$

The net ("net") directional connectedness from market i to all other markets j:

$$S_i^g(H) = S_{\cdot i}^g(H) - S_{i\cdot}^g(H) \tag{6.6}$$

Finally, the net pairwise connectedness from market i to market j:

$$S_{ij}^g(H) = \left(\frac{\tilde{\theta}_{ji}^{g}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^{g}(H)} - \frac{\tilde{\theta}_{ij}^{g}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^{g}(H)} \right) \cdot 100 = \left(\frac{\tilde{\theta}_{ji}^{g}(H) - \tilde{\theta}_{ij}^{g}(H)}{N} \right) \cdot 100 \tag{6.7}$$

Regarding parameters setting, we follow Diebold and Yilmaz (2014), using p = 3 for lag structure, H=12 for horizon of underlying variance decomposition and W=100 days for size of overlapping window when computing rolling indices.

6.3 Data and preliminary analysis

Our sample period is from January 01, 2013, to December 31, 2020, a total of 2015 daily observations. Following Akhtaruzzaman et al. (2021), the starting point was defined so that the pre-COVID-19 period did not overlap the global financial crisis (2007-2009) or the European sovereign debt crisis (2010-2012). The end point was the last available. We assume COVID-19 period begins on December 31, 2019, the day cases of pneumonia[11] detected in Wuhan, China, are first reported to the WHO. This period ends on December 31, 2020, the end of our sample.

The raw data is comprised of daily percent returns of 11 US sectoral indices formed by the companies included in the S&P 500 index and classified as members of each of the sectors under the Global Industry Classification Standard (GICS). Namely, we use the indices

[11] 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).

S&P 500 Consumer Discretionary (SPLRCD), Consumer Staples (SPLRCS), Energy (SPNY), Financials (SPSY), Health Care (SPXHC), Industrials (SPLRCI), Information Technology (SPLRCT), Materials (SPLRCM), Real Estate (SPLRCREC), Telecom Services (SPLRCL) and Utilities (SPLRCU). The data is provided by Investing.com[12].

All considered indices are market cap weighted and quarterly rebalanced, implying that the weight of specific companies, and which companies are considered in the indices, evolve along the sample. We understand this fact should not be corrected for, once the data already provides a valid proxy for sectoral performance, the weighted returns of representative stocks at the moment. It should also be noted that this weighting method is usual for broad market indices, and that most empirical literature does not correct for rebalancing.

Figure 6.1 show the cumulative and daily returns on the considered indices. In all series, we can see increase in volatility during the COVID-19 period. Particularly, daily maximums and minimums returns occurred during the pandemic for all indices. It is also noteworthy the fact that the March 2020 COVID-19 induced drawdowns have been of greater magnitude than those observed in the much longer pre-COVID-19 period.

We transform the raw data to get the variables of interest, price volatilities. Put in another way, in the present study the vector of variables of interest, x_t, represents price volatilities from sectoral indices in the US. As with Antonakakis et al. (2018) and Corbet, Goodell, and Günay (2020), among others, we define[13] the index i price volatility as the absolute return $V_{it} = |\ln P_{it} - \ln P_{it-1}|$, where P_{it} is the closing value of index i price on day t. We have detected a few structural breaks in the dataset using CUSUM tests, both on the pre-COVID-19 (Energy, IT and Utilities) and on COVID-19 period (Health care and Staples). Thus, we have included dummy variables in our model to account for these breaks.

Table 6.2 shows descriptive statistics based on sectoral price volatility from pre-COVID-19 and COVID-19 periods. We highlight that considerable increase of mean volatility is observed across all indices from pre-COVID-19 to COVID-19 period. The same increasing behavior applies to second, third and fourth moments of return volatilities, indicating a pattern of higher levels of dispersion, asymmetry, and kurtosis for the variable of interest during the pandemic. We also highlight that the Augmented Dickey-Fuller (ADF) test ensures stationarity of all VAR components.

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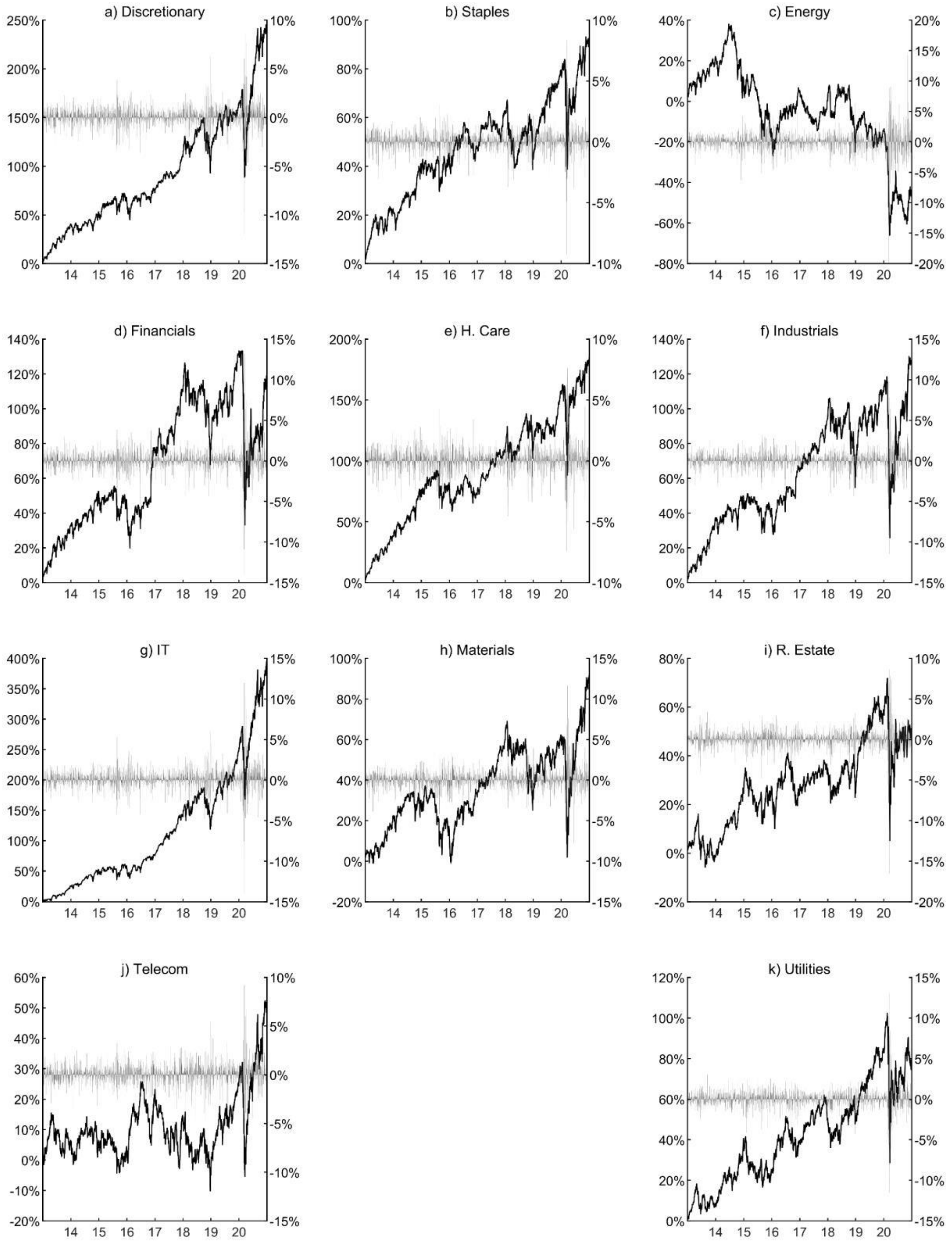
[12] We have performed a data quality check, by comparing the used data with that available on the S&P global website. We have found only very few and small differences that are due to rounding.

[13] For a background on the advantages of using absolute return as a measure of volatility, refer to Forsberg and Ghysels (2007). In the robustness section, however, we also analyze the effects of using conditional volatilities.

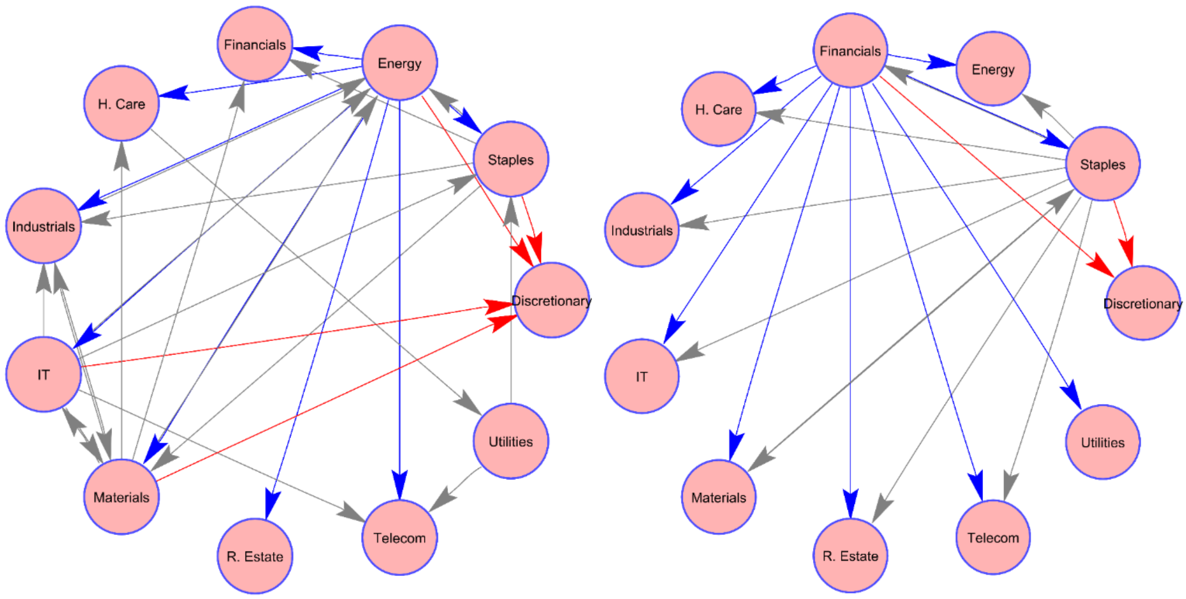
Figure 6.1 – Cumulative and daily percent returns of US sectoral indices.



Notes: The black line (left scale) represents cumulative returns. The grey bar plot (right scale) refers to the percent returns.

Figure 6.2 – Pairwise Granger causality relationship of price volatility (at the 5% significant level).

a) Pre COVID-19 period b) COVID-19 period



The ARCH LM test points heteroscedasticity in the data. This should not hinder the present study, since the OLS estimation of the VAR coefficients upon which the underlying variance decomposition relies remain consistent under this circumstance, as discussed in Engle (1982).

In this stage we study the lead-lag relationship of the volatilities using a Granger causality test. For brevity, the results are reported only in a network plot, Figure 6.2, which is based on Zhang (2017). To perform this exercise, we used a VAR[14] including all series simultaneously, then tested the null hypothesis that the coefficients of lagged index i where jointly zero on equation for index j, for $i, j = 1,2, \ldots ,11$. If the null hypothesis is rejected, index i granger causes index j. The arrows in Figure 6.2 follow the direction of causality. Thus, in the pre-COVID-19 period the Energy sector causes all the other sectors except for Utilities, while the Consumer Discretionary sector is the most frequently granger caused. During the COVID-19 period Financials causes all the remaining sectors while Consumer Discretionary is again one of the most caused sectors.

[14] We selected the most adequate lag structure using the Akaike Information Criterion.

6.4 Empirical results

6.4.1 Comparative static analysis

The price volatility connectedness tables of both pre-COVID-19 and COVID-19 periods are presented in Table 6.3. There are several points worth noting of which we highlight some.

First, total connectedness in the COVID-19 period, 84.5%, is much higher as compared to the pre-COVID-19 period, 65.9%. This increase is associated with a higher systemic risk during the pandemic as discussed in Diebold and Yilmaz (2014). There are many candidates causes for the increase of sectoral connectedness during COVID-19, among usual factors expected in crises in general, as herd behavior, fire sales, policy action and feedbacks (Diebold and Yilmaz, 2015) as well as factors idiosyncratic of this pandemic, as the lockdown induced economic activity retraction or loss of job productivity discussed in Goodell (2020). From an asset pricing perspective, as discussed in Diebold and Yilmaz (2015) and Dungey et al. (2011), time varying connectedness could come from time variations of common factor loadings or of factor structure in a factor model.

Second, there are some radical changes in the connectedness of some indices. For instance, Utilities and Real State were the sectors that least received from the system in pre-COVID-19 period, with connectedness "from" of 41.3% and 56.9% respectively, while were the sectors that received the most from the system in COVID-19 period, 87.3% and 86.7%. Third, Industrials (Telecom) has been the sector with the highest (lowest) "net" connectedness with 18.6% (-19.1%) during pre-COVID-19 while during COVID-19 Industrials (Utilities) has been the sector with the highest (lowest) net connectedness, with 24.5% (-39.2%).

Fourth, Financials has increased its "net" connectedness by 7.5%, the highest jump among sectors with positive "net" connectedness on the pre-COVID-19 period. This result seems to corroborate Akhtaruzzaman et al. (2021) results that highlight the importance of financial sector to contagion transmission during COVID-19 pandemic in an international context. These last three points indicate that, in addition to a system wide change in the connectedness of the sectors, there have been considerable asymmetric changes across sectors and potentially in a pairwise manner.

To further investigate the changes in the directional pairwise net connectedness level, we use network representations in Figure 6.3, with all connections, and in Figure 6.4, only with the connections in the upper two deciles of magnitude, both in pre-COVID-19 and COVID-19 periods.

Table 6.2 – Descriptive statistics based on sectoral price volatility (by denoted period).

Panel A: Basic information - Pre-COVID-19 period (January 1, 2013–December 30, 2019)

	SPLRCD	SPLRCS	SPNY	SPSY	SPXHC	SPLRCI	SPLRCT	SPLRCM	SPLRCREC	SPLRCL	SPLRCU
Mean	0.0067	0.0054	0.0091	0.0074	0.0067	0.0067	0.0075	0.0075	0.0067	0.0073	0.0066
Std	0.0063	0.0049	0.0084	0.0070	0.0062	0.0063	0.0075	0.0067	0.0061	0.0067	0.0057
Skewness	2.1764	1.7861	1.8013	1.9567	1.8139	1.8511	2.0774	1.6634	1.8151	1.9870	1.7349
Kurtosis	10.5260	7.7608	7.5038	8.7920	7.8241	8.0486	9.1688	6.6086	7.8985	9.1113	7.9025
Observations	1,761	1,761	1,761	1,761	1,761	1,761	1,761	1,761	1,761	1,761	1,761
Jarque-Bera	5546.1***	2599.3***	2440.6***	3585.2***	2673.2***	2875.9***	4058.8***	1767.5***	2727.6***	3899.1***	2646.9***
Q(10)	582.86***	273.52***	444.64***	252.74***	419.29***	302.21***	506.85***	436.02***	228.17***	111.79***	70.632***
ADF	-19.76***	-19.89***	-20.27***	-20.49***	-19.99***	-20.70***	-20.73***	-19.31***	-20.41***	-21.06***	-20.57***
ARCH LM	42.404***	58.028***	43.747***	55.374***	40.167***	35.468***	73.238***	70.875***	74.098***	14.375***	11.791***

Panel B: Basic information - COVID-19 period (December 31, 2019–December 31, 2020)

	SPLRCD	SPLRCS	SPNY	SPSY	SPXHC	SPLRCI	SPLRCT	SPLRCM	SPLRCREC	SPLRCL	SPLRCU
Mean	0.0139	0.0105	0.0254	0.0187	0.0122	0.0161	0.0168	0.0162	0.0163	0.0135	0.0151
Std	0.0160	0.0142	0.0287	0.0221	0.0150	0.0191	0.0194	0.0181	0.0200	0.0156	0.0193
Skewness	3.2077	3.1552	2.9818	2.8606	2.7185	2.7549	3.0553	2.7623	3.5086	2.7334	3.0257
Kurtosis	18.0231	14.8712	15.8545	13.4546	12.1044	12.7486	15.9023	13.0927	22.2721	13.2080	14.0519
Observations	254	254	254	254	254	254	254	254	254	254	254
Jarque-Bera	2824.1***	1912.9***	2125.1***	1503.1***	1190.1***	1327.0***	2156.9***	1401.0***	4451.9***	1419.0***	1680.2***
Q(10)	376.57***	618.36***	185.25***	524.26***	536.06***	455.09***	361.85***	453.22***	475.24***	326.44***	681.26***
ADF	-7.260***	-6.416***	-8.232***	-6.214***	-6.919***	-6.870***	-6.810***	-6.690***	-6.637***	-6.859***	-6.340***
ARCH LM	11.120***	91.340***	0.3758	50.017***	48.256***	18.876***	63.866***	14.859***	17.439***	68.908***	46.091***

Notes: The above data represents daily sectoral price volatility for the period of January 2013 through December 2020. Data was obtained from Investing.com. *** denotes 1% level of significance. The Jarque-Bera test is used to check whether the price volatilities distribution is normal. The Box-Pierce-Ljung Q(10) statistic is distribute as a χ^2_{10} and test for autocorrelation. The augmented Dickey Fuller (ADF) is used to check the presence of unit roots. The ARCH LM test is used to investigate presence of heteroscedasticity, its null hypothesis is no ARCH effect.

In both Figure 6.3 and Figure 6.4 the arrows go from the sector with positive net pairwise connectedness to its counterpart. Thus, for instance, Industrials sector possess positive net pairwise connectedness with all other sectors during the COVID-19 pandemic.

Figure 6.3 – All pairwise net directional connectedness of price volatility.
a) Pre COVID-19 period b) COVID-19 period

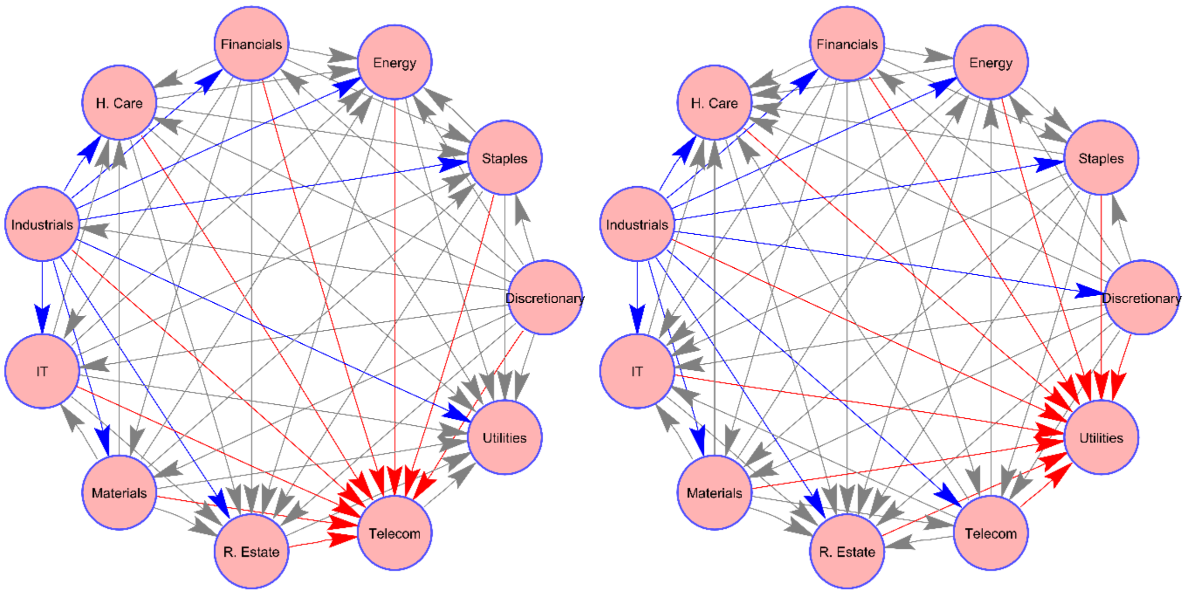


Figure 6.4 – Most relevant pairwise net directional connectedness of price volatility.
a) Pre COVID-19 period b) COVID-19 period

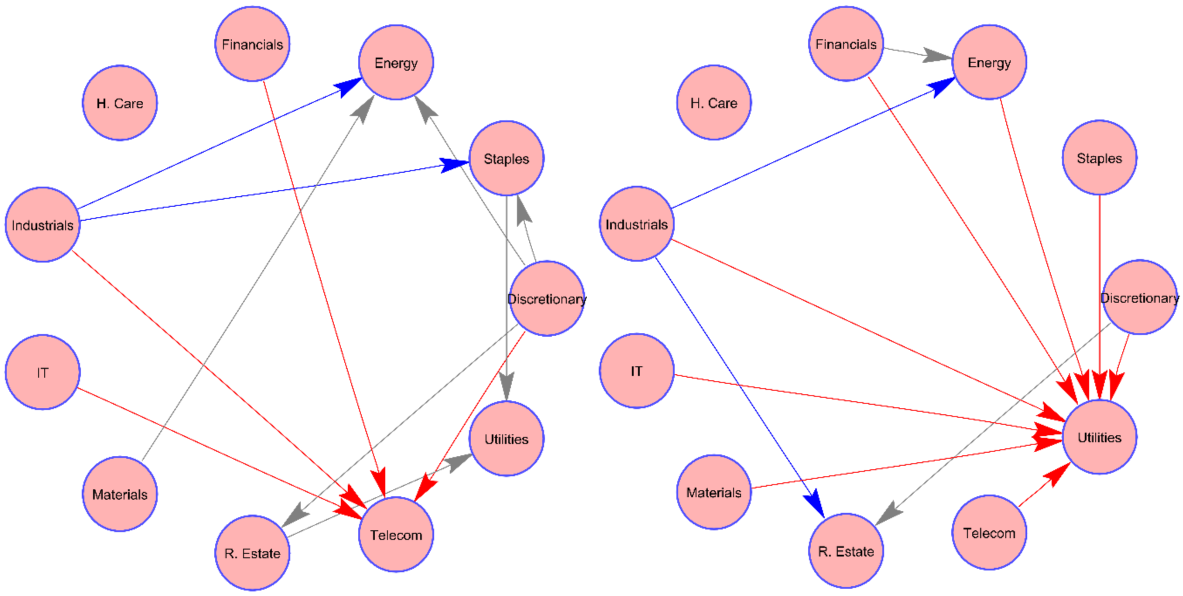


Figure 6.3 underline the fact that some considerable changes has been taking place during COVID-19 in the directional pairwise relations. In Figure 6.4 we can see that in the upper tail of pairwise connectedness the changes are even more pronounced during COVID-19. In fact, only 2 out of 12 of the connections that were among the most relevant before the

COVID-19 remained in the top two deciles during the pandemic, namely Industrials-Energy and Discretionary-Real State. It is also apparent that there is a considerable concentration of strong pairwise connectedness to Utilities after COVID-19.

6.4.2 Dynamic analysis

6.4.2.1 Total Connectedness Rolling Window Plot

The previous section provided snapshots of both pre-COVID-19 and COVID-19 period, in a static form. It is arguable, though, that relationships are dynamically changing, mainly if one considers the possibility that the impact of COVID-19 over stock market has evolved considerably as it happened. To study the connectedness dynamics, we use rolling estimation windows of the connectedness indices.

We start by plotting the price volatility total connectedness over 100-day rolling-sample windows in Figure 6.5.

Figure 6.5 – Rolling total connectedness of price volatility.

Note: The rolling estimation window width is 100 days, and the predictive horizon for the underlying variance decomposition is 12 days.

We first notice that there is considerable changing in the rolling windows estimation of total connectedness over time. The full sample extremes are 44.4% and 90.0%, against an unconditional mean of 65.9% before the pandemic and 84.5% during the COVID-19 period.

Observing the Figure 6.5, one can see a reasonably stable period from the end of May 2014 to mid-August 2015, where connectedness oscillates in the range of 57.0% to 78.7%, followed by a significant increase of more than 20 points to 83.9% in the end of August 2015. This first considerable spike can be associated with turbulences in the US market due to spillovers of the China stock market crash occurred on August 24, 2015. The increased connectedness here observed indicates contagion from China to various sectors of US economy, likely with both economic and financial roots, as failing supply chain, depressed demand, as forced fire sales of invested assets and increased credit delinquency.

Beginning in mid-January 2016, there is a quasi-monotonic decay to the sample minimum, 44.4%, on January 12, 2018, which is followed by a huge spike on connectedness to pre-COVID maximum of 85.3% on February 5, 2018. On this day DJI plunged 1,175 points (4.60%), the biggest drop in points up to that moment during a single day, amid concerns with inflation and potential rising of interest rates. Put it differently, this spike in connectedness coincides with fears of a tightening on monetary policy with impact over the of long-term interest rates, similarly to findings of Diebold and Yilmaz (2014).

After this point to the beginning of COVID-19 period, there has been alternating tranquil and turbulent moments, associated, for instance, with China-US trade tensions. Economically, the unstable connectedness of this period is in accordance with the view that bilateral trade linkage is a relevant factor for financial spillovers, as expressed in Ito and Hashimoto (2005).

Examining the COVID-19 period, the first noticeable feature of connectedness is the entire sample maximum of 90.0%, reached on February 27, 2020. On this day DJI has dropped 1,190 points (4.42%) after negative returns in the five previous trading sections, reaching a cumulative drop of 3,581 points (12.3%) since February 19, 2020 close. This early pandemic turmoil happened amid fears caused by a surge in COVID-19 cases outside China and the US report of the first case with no known travel link in northern California, on February 26, 2020. From this point on up to the end of July 2020 (day 23), the total connectedness was sustained in levels only seen during the COVID-19 period, including the acute crash of February 2018.

From august to the end of the sample we observe a gradual reduction in the connectedness levels, what is simultaneous to markets improvements driven, among other factors, by FED actuation, Government stimulus efforts, vaccines good news and subsequent FDA emergency approvals. At this point, it is fair to say that many uncertainties related to this pandemic have been resolved, with consequent improvements of markets and decrease of connectedness. However, it is unfortunately too soon to completely grasp how the pandemic will evolve from this point. Thus, it is probably premature to speculate on near future developments on sectoral connectedness as well.

Table 6.3 – Connectedness table based on sectoral price volatilities (by denoted period).

Panel A: Connectedness table for pre-COVID-19 period (January 1, 2013–December 30, 2019)

	SPLRCD	SPLRCS	SPNY	SPSY	SPXHC	SPLRCI	SPLRCT	SPLRCM	SPLRCREC	SPLRCL	SPLRCU	*FROM*
S&P 500 Consumer Discretionary (SPLRCD)	25.1	5.8	4.9	10.0	10.0	12.0	14.1	9.6	3.4	4.2	0.8	74.9
S&P 500 Consumer Staples (SPLRCS)	8.7	33.5	3.7	7.4	8.8	8.2	6.4	6.3	6.9	5.3	4.7	66.5
S&P 500 Energy (SPNY)	7.9	4.9	39.2	6.8	5.7	9.0	6.4	12.9	2.4	3.0	1.6	60.8
S&P 500 Financials (SPSY)	11.0	5.8	4.9	26.4	9.3	13.9	10.1	10.4	3.6	3.4	1.3	73.6
S&P 500 Health Care (SPXHC)	11.5	7.4	4.1	9.9	29.0	10.8	10.5	8.1	4.0	3.4	1.5	71.0
S&P 500 Industrials (SPLRCI)	12.0	5.8	5.7	12.4	9.1	23.8	11.1	12.6	2.8	3.8	1.0	76.2
S&P 500 Information Technology (SPLRCT)	15.0	4.9	4.5	10.2	10.0	12.2	26.1	9.3	2.6	4.4	0.8	73.9
S&P 500 Materials (SPLRCM)	10.4	5.3	8.8	10.5	7.4	14.1	9.2	27.8	2.5	3.2	1.0	72.2
S&P 500 Real Estate (SPLRCREC)	6.5	9.3	2.7	5.8	6.3	5.1	4.4	4.0	43.1	4.1	8.9	56.9
S&P 500 Telecom Services (SPLRCL)	8.2	7.1	3.8	5.8	5.6	7.1	7.5	5.2	4.2	42.7	2.9	57.3
S&P 500 Utilities (SPLRCU)	2.3	8.1	2.2	2.9	3.5	2.5	1.9	2.3	12.2	3.4	58.7	41.3
TO	93.4	64.4	45.3	81.7	75.8	94.8	81.5	80.7	44.7	38.2	24.4	**65.9**
NET	18.4	-2.0	-15.5	8.1	4.7	18.6	7.6	8.4	-12.3	-19.1	-16.9	

Panel B: Connectedness table for COVID-19 period (December 31, 2019–December 31, 2020)

	SPLRCD	SPLRCS	SPNY	SPSY	SPXHC	SPLRCI	SPLRCT	SPLRCM	SPLRCREC	SPLRCL	SPLRCU	*FROM*
S&P 500 Consumer Discretionary (SPLRCD)	15.7	9.0	5.9	8.8	8.3	10.5	11.3	8.6	6.2	11.6	4.0	84.3
S&P 500 Consumer Staples (SPLRCS)	10.5	15.8	6.3	9.3	9.3	9.6	9.1	8.3	6.3	9.8	5.6	84.2
S&P 500 Energy (SPNY)	8.1	5.7	21.8	13.4	5.8	13.7	5.4	10.7	5.8	6.2	3.3	78.2
S&P 500 Financials (SPSY)	9.6	8.3	8.9	15.5	7.2	13.0	6.7	10.3	8.2	7.5	4.8	84.5
S&P 500 Health Care (SPXHC)	10.2	11.5	5.9	8.5	14.2	9.9	9.4	9.2	6.4	9.4	5.5	85.8
S&P 500 Industrials (SPLRCI)	9.7	7.9	9.1	12.4	7.6	15.7	6.9	11.1	7.8	6.9	4.7	84.3
S&P 500 Information Technology (SPLRCT)	12.7	10.7	5.7	8.0	9.3	9.7	14.6	8.5	5.5	11.7	3.6	85.4
S&P 500 Materials (SPLRCM)	9.6	8.4	8.1	10.9	8.4	12.2	7.8	14.2	7.3	7.7	5.5	85.8
S&P 500 Real Estate (SPLRCREC)	9.9	9.2	6.6	11.0	7.4	11.0	7.0	9.7	13.3	7.7	7.3	86.7
S&P 500 Telecom Services (SPLRCL)	12.6	10.4	5.4	8.4	9.0	9.6	11.2	7.7	5.6	16.4	3.7	83.6
S&P 500 Utilities (SPLRCU)	9.7	11.4	6.3	9.4	8.4	9.6	7.2	9.2	8.1	8.0	12.7	87.3
TO	102.5	92.4	68.2	100.1	80.6	108.8	82.1	93.4	67.2	86.6	48.2	**84.5**
NET	18.2	8.2	-10.0	15.6	-5.2	24.5	-3.3	7.7	-19.6	3.0	-39.2	

Note: The predictive horizon is 12 days. The ij-th entry of the upper-left 11 x 11 sector index submatrix gives the ij-th pairwise directional connectedness, i.e., the percent of 12-day-ahead forecast error variance of firm i due to shocks from firm j. The rightmost (FROM) column gives total directional connectedness (from), i.e., off diagonal row sums. The bottom (TO) row gives total directional connectedness (to), i.e., off diagonal column sums. The bottommost (NET) row gives the difference in total directional connectedness (to – from). The bottom-right element (in boldface) is the total connectedness.

Regarding potential economic implications of unprecedented connectedness found, one possible mechanism could be through failing credit supply. This is because this increase may have a role to play in the instability of financial market institutions. Nevertheless, we understand these implications have largely been mitigated by liquidity injections made by the central banks and governments worldwide. Put it another way, as COVID-19 is first of all an economic and secondly a financial crisis (Bouri et al., 2021), the fast acting of authorities following GFC experience have been providential to attenuate a possible feedback from financial system. Overall, we feel our findings have been more of a consequence than cause of further economic turmoil.

6.4.2.2 Directional Connectedness Rolling Window Plots

In this section we analyze the dynamic behavior of total directional - "to", "from" and "net" - connectedness for all US sectoral indices. The underlying plots are presented in the three panels of **Figure 6.6**.

We first evidence the fact that directional "from" connectedness is much smoother across sectors when compared to the "to" connectedness, what is in accordance with what is reported in Diebold and Yilmaz (2014), while analyzing the connectedness of 13 US financial institutions during the GFC. This fact is due primarily to asymmetric size and centrality of the sectors in US economy, which makes the spillovers of shocks to different sectors to have a wide range of responses.

Second, we observe that the "from" connectedness of all sectors finds its maximum during the COVID-19 period, in a pattern similar to that discussed in the previous section for the total connectedness index. On the other hand, the "to" connectedness reached the maximum during COVID-19 period for 6[15] out of the 11 indices studied, although there is a clear spike for all the indices surrounding February 27, 2020. We understand these findings indicate that COVID-19 had a homogeneous and unprecedented effect across sectors with regard to openness to other sectors spillovers while had a generally strong but asymmetric effect across sectors in regard to sending spillovers.

Considering the asymmetric nature of contribution from each sector to others, it is worth to highlight that the Energy sector have shown the highest maximum values of "to" connectedness, 223%[16], despite presenting modest average contributions both before (45.3%)

[15] The Consumer Discretionary, Energy, Financials, Industrials, IT and Telecom Services sectors have reached its highest "to" connectedness during COVID-19.

[16] As the "to" connectedness are sums of errors variances shares in forecasting 10 sectors due to the remaining

and during the COVID-19 period (68.2%). This fact may be related to the findings of Zhang (2017) that show that oil prices are generally net receivers from stock markets but can contribute significantly when large shocks occur. Financials shows the second highest maximum, 195%, what is in accordance with the common view that this is a sensible sector in crisis scenarios.

Third, turning now to the “net” connectedness, we highlight that most sectors maintained their status as predominantly net receivers/senders of connectedness during COVID-19 as compared to pre-COVID-19 period, the only two exceptions were IT and Health Care both of which were predominantly net senders (receivers) before (during) the pandemic. For instance, the Energy sector had positive “net” connectedness during 23.0% (35.6%) of the time before (during) the pandemic making it a predominantly net receiver of connectedness from the system in both periods. Once more we highlight the Financial sector, that was a net sender of connectedness in 67.8% (88.9%) of the time before (during) the COVID-19 period, having experienced the highest growth in that proportion among all sectors.

6.5 Robustness check

To examine sensitivity to parameters definition, we compute the rolling total connectedness index using the baseline parameters - window width (W) of 100 days, predictive horizon for the underlying variance decomposition (H) of 12 days and VAR lag structure (p) of 3 – and close values. The results are in Figure 6.7. There we can see that most of the time the 25%-75% quantiles range of the obtained distributions is very narrow and contains the baseline value and that even the extremes maintain a generally close relation to baseline computation.

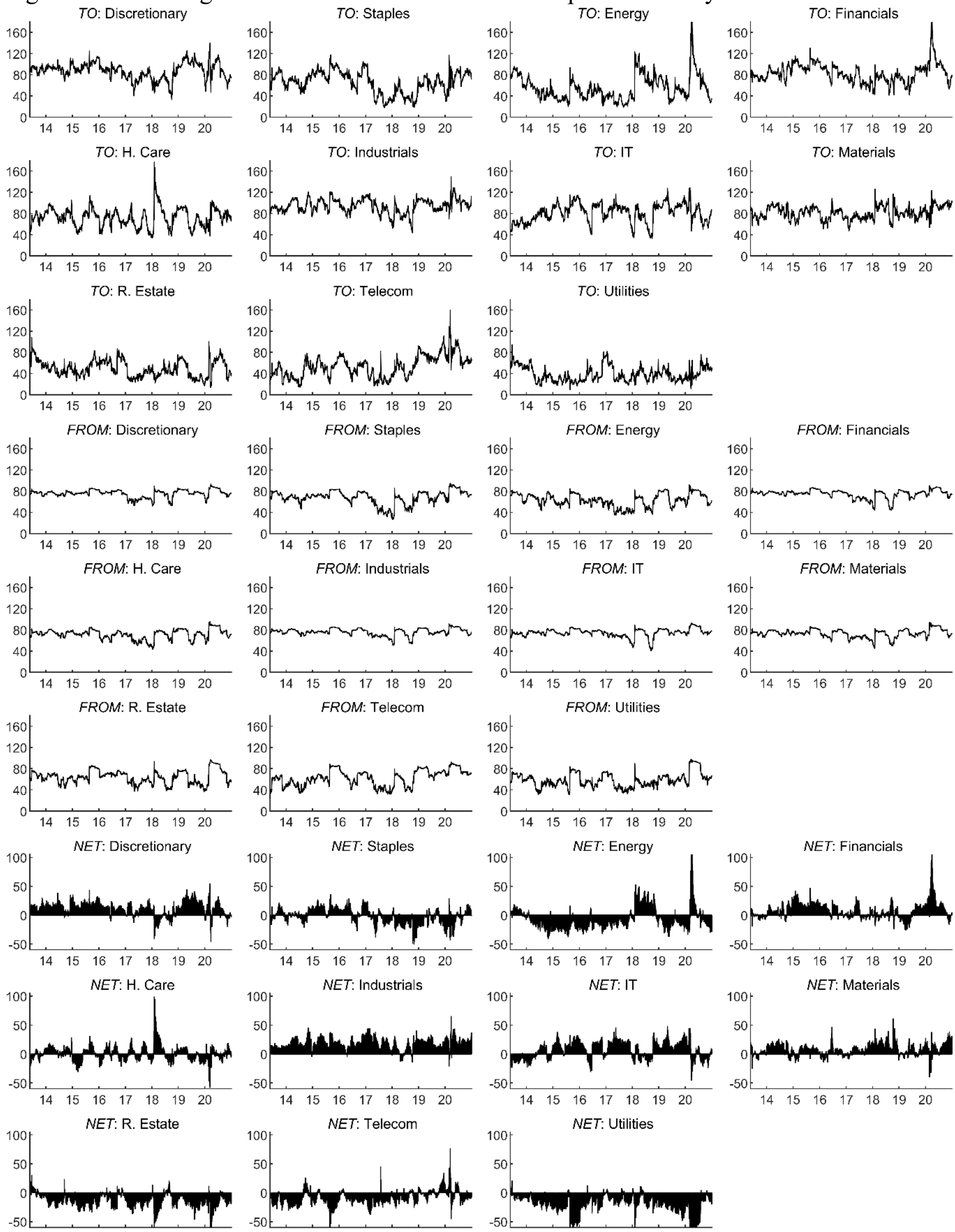
We also examine the effects of using an alternative definition of volatility over the measure of total connectedness. The results are in Figure 6.8. Following Antonakakis et al. (2018), we use conditional volatilities. We obtained the conditional volatilities extracted from best fit univariate volatility models[17]. Figure 6.8 is remarkably similar to Figure 6.7. Particularly, all the features discussed in the section 4.2 remain present.

Finally, to check if the results were driven by outliers, we used the moving average of the returns volatilities as the variables of interest and recomputed the total connectedness index. In this configuration, the features discussed on section 4.2 once more hold. For brevity, the related plots are not reported and will be provided from authors upon request.

sector, its value is not limited to 100%.

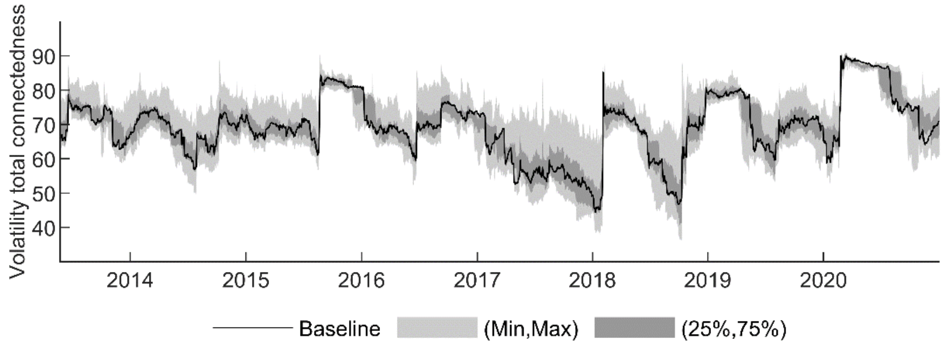
[17] Considering the characteristics of financial data, we searched for each index the best model among ARCH, GARCH, A-GARCH, TARCH and A-TARCH alternatives using the Akaike Information Criterion as a selector.

Figure 6.6 – Rolling total directional connectedness of price volatility.



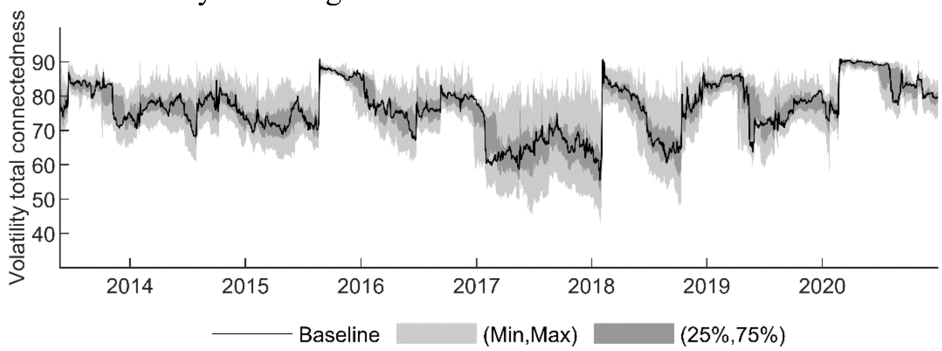
Note: The rolling estimation window width is 100 days, and the predictive horizon for the underlying variance decomposition is 12 days. Total “to” (“from” /”net”) connectedness is shown in the upper (middle/bottom) panel.

Figure 6.7 – Sensitivity of rolling total connectedness to parameters of the model.



Note: Baseline refers to computation of total connectedness with parameters set to window width (W) of 100 days, predictive horizon for the underlying variance decomposition (H) of 12 days and VAR lag structure (p) of 3 while maintaining the usual volatility definition as the absolute log returns. We also compute the rolling total connectedness using a grid of parameters, namely all triplets (W, H, p) with W, H, and p in {75,100,125}, {6,12,18}, {2,3,4} respectively. (Min , Max) and (25%, 75%) refer to the extremes and 25%-75% quantiles of the obtained distribution.

Figure 6.8 – Sensitivity of rolling total connectedness to alternative definition of volatility.



Note: Baseline refers to computation of total connectedness with parameters set to window width (W) of 100 days, predictive horizon for the underlying variance decomposition (H) of 12 days and VAR lag structure (p) of 3 while defining volatility as the conditional volatility obtained from best fit univariate GARCH type models. We also jointly examine sensitivity to parameters definition, computing the rolling total connectedness using a grid of parameters, namely all triplets (W, H, p) with W, H, and p in {75,100,125}, {6,12,18}, {2,3,4} respectively. (Min , Max) and (25%, 75%) refer to the extremes and 25%-75% quantiles of the obtained distribution.

6.6 Conclusions

The COVID-19 pandemic provides a unique backdrop to re-examine connectedness between economic sectors during crises, even more so if one considers the concomitant Russia-Saudi Arabia oil price war. Adding to the literature on financial markets effects of COVID-19, employing the connectedness indices of Diebold and Yilmaz (2009, 2012, 2014), we develop comparative static and dynamic analysis of the price volatility connectedness of US sectoral indices aiming to unveil quantitative and - possibly - qualitative changes and stylized facts occurred during an exceptional crisis period. The pre-COVID-19 is chosen to be January 01, 2013 to 30 December 2019, a relatively stable period not overlapping the last major economic crisis. The COVID-19 period is from December 31, 2019 to December 31, 2020.

Among several results, we find there has been extraordinary increase in connectedness among US sectoral indices volatility during COVID-19, lasting from earlier stages of international spread of cases in the end of February to the end of July, 2020. This increase aligns with the observed behavior in previous crises as reported in Baruník et al (2016) and Mensi et al. (2020), for instance; unprecedented and homogeneous increase in how much volatility spillovers each one of the indices receives from the system; a considerable but asymmetric increase in how much spillovers each index sends to the system; qualitatively, considerable changes in pairwise relationships, especially among the connectedness links in the upper two deciles of magnitude, however, in a total net connectedness perspective, there is little evidence of structural changes in relationships - in the sense that most indices have maintained their status as net senders/receivers of connectedness to the system during the pandemic as compared to the previous tranquil period; the Energy sector reached the highest daily value of connectedness “to” the system, even being an average net receiver of connectedness both before and during the pandemic in accordance with Zhang(2017) perceptions; the Financials sector has shown to be relevant sender of connectedness during the pandemic in several metrics.

Regarding practical use, our findings seem to indicate a unprecedent increase in the network connectedness of US sectors during a severe crisis moment. The implication would be that little sectoral diversification advantage could eventually be expected in such harsh moments. Risk managers gain in verify how extreme sectoral connectedness can be in practice, and consequently adjusting stress tests scenarios. Asset pricing models could benefit of considering sectoral factors during turbulent moments.

For the policy makers, first, the results indicate relevance of specific sectors during turbulent periods, in particular, the sectors that send spillovers more intensely and those that are the most prone to receiving them. This identification could be used to target supporting and possibly macroprudential type policies. Second, as the increase of connectedness seems to indicate crisis intensity, the dynamic analysis could serve as real-time crisis monitoring instrument, as suggested in Diebold and Yilmaz (2015).

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