Department of Economics

Group for Economic Analysis at Reading (GEAR)

COVID-19 Cases and Stock Prices by Sector in Major Economies: What Do We Learn from the Daily Data?

by Hussein Hassan, Minko Markovski and Alexander Mihailov

Discussion Paper No. 2022-04

Department of Economics
University of Reading
Whiteknights
Reading
RG6 6AA
United Kingdom

www.reading.ac.uk

COVID-19 Cases and Stock Prices by Sector in Major Economies: What Do We Learn from the Daily Data?

Hussein Hassan,[*] Minko Markovski[†] and Alexander Mihailov[‡]

April 2022[§]

Abstract

This paper is the first to empirically uncover, via a recent GARCH-based estimation technique addressing the problem of dimensionality, volatility correlations and Granger causality between the daily COVID-19 cases and the share price indexes in all 11 sectors of the Global Industry Classification Standard across 11 major world economies accounting for 83.1% of the global stock market capitalization for the two full years of the current global pandemic, January 2020 – December 2021. We document a shift of density mass from dominantly negative correlations by sector from the first and second halves of 2020, with no vaccines to reassure human fear, to dominantly positive correlations in the first and second halves of 2021, with the population vaccinated two or three times and recovering its optimism. Granger causality tests reveal almost immediate news transmission, of a day or two, from the COVID-19 cases to sectoral price indexes, with some common patterns but also some heterogeneity by sector and country. We interpret the documented main trends and findings by the usual story of how societies learn: faced with an unexperienced danger and no cure for the virus, people panicked all over the world in 2020, influencing share prices dominantly in a negative direction; by contrast, once equipped with vaccines and feeling reassured for the longer run, optimism recovered in 2021, and stock prices, including by sector, too.

Keywords: COVID-19 cases, share price sectoral indexes, empirical volatility correlations, Granger causality, daily-frequency GARCH-based estimation, waves of pessimism and optimism, social learning about the death toll of a pandemic, public health panic versus reassurance

JEL classification: E71, F41, G01, G15, G18, G41

[*]Department of Economics, University of Reading, Whiteknights, Reading RG6 6EL, United Kingdom; hussein.hassan@reading.ac.uk

[†]Department of Economics, University of Reading, Whiteknights, Reading RG6 6EL, United Kingdom; m.t.markovski@pgr.reading.ac.uk; and Central Bank of the UAE, PO Box 854, Abu Dhabi, United Arab Emirates.

[‡]Corresponding author: Department of Economics, University of Reading, Whiteknights, Reading RG6 6EL, United Kingdom; a.mihailov@reading.ac.uk

[§]First draft: March 2022; preliminary draft: February 2022. We thank for useful feedback Stefania Lovo and participants in a seminar at Reading. The usual disclaimer applies; in particular, we represent our own views as academic researchers and not those of the Central Bank of the UAE.

Contents

List of Figures

List of Tables

1 Introduction and Scarce Closest Literature

Share price movements at stock exchanges worldwide have always been at the centre of interest of investors, businesses and households. More precisely, the driving force behind this interest, as Keynes (1936) has notably pointed out, are perceptions of risks and opportunities, waves of optimism and pessimism regarding the course of the real economy and its financial system. Furthermore, it has been acknowledged long ago – see, e.g., Mindell (1961) – that the difficulty to foresee market movements of security prices arises from the many influences upon them. A related concern to the same author was that a researcher would hardly be able to convincingly isolate one variable, ‘the news’, as ‘the cause’ out of the bundle of covariates of what he calls ‘the causal complex’ (p. 34) – a task for which many alternative and complementary econometric techniques have indeed competed.

Financial markets, in a broader sense, and stock exchanges, in particular, have been viewed as playing a key role in (potentially) transferring productive or purchasing power and accumulated wealth from the present to the future, over a medium and long run, mostly. Like many phenomena in life or science – for instance, nuclear energy – financial markets and stock exchanges can be used for good or bad, with constructive or destructive aims or consequences. Accordingly, they are often praised as institutional mechanisms that enable market signals and price discovery, channelling investment in a society; or blamed for greed, misfortune and erratic waves of euphoria and panic, costing bankruptcies for millions of firms or families.

Now, in the 21st century, we live in ‘the information age’, the age of the Internet and instantaneous access to all sorts of ‘big data’, social media, traded products, or policy opinions. But at least since the Industrial Revolution and the advent of the market economy in democratic societies, data on prices and transaction volumes have always been vital for any decision-maker, be it as commonplace as a household or as unique in its function as a central bank. Indeed, prices perform the role of market signals, and in such a way inform and enable transactions in goods, services, real and financial assets across the world. To perform the role of a market signal that guides efficient allocation of scarce resources and investment opportunities, prices of expected discounted future cash-flows, in the case of equity trading, have to be competitive, that is, ‘fair’, emerging as equilibrating demand and supply, similarly to the price for a particular good or service at any point in time. Such a price formation, or discovery, appears as if fixed precisely, even if only temporarily (and then it continues to evolve as news keep on arriving), to clear total supply and total demand, e.g., as if resolved by the mythical figure of the Walrasian Auctioneer of the Ecole de Lausanne and his central, clearing house role in the implied ‘tâtonnement’ (‘groping’, in French) process of price discovery (Walras, 1874–1877). To put it in a more usual language, prices – including share prices – reflect, instantaneously, prevailing information and expectations in a market with regard to present and future relative scarcity, technological progress, profitability of firms and sectors.

Along such lines of thought, Wagner (2020) eloquently writes:

> "Many people do not have much sympathy for the stock market; they associate it with greed, scandals and speculation. Yet the stock market can be a powerful tool for society. It provides a unique view of the expected future of a company and the economy. That is because the value of a firm derives from all future expected cash flows, discounted to the present to adjust for time and uncertainty. In the financial markets, all kinds of individuals meet, sophisticated and naïve, opinionated and without convictions, to play a high-stakes game: the pricing game. Through a mix of fundamental value-drivers and simple demand-and-supply dynamics, asset prices emerge. Effectively, the stock market is an incentivized survey of future expected outcomes. It is precisely in complex and fast-evolving situations that the stock market provides particularly useful information."

And, shifting attention to relative share prices and stock-market sectors, he concludes:

> "The outbreak of COVID-19 is bringing about epochal changes to our lives. [...] In such a moment of collective confusion, what do we learn from the stock market? One might be tempted to say 'not much'. [...] But digging deeper, one recognizes additional, arguably more important patterns. Specifically, even as the aggregate market experiences feverish fluctuations or falls strongly, the relative stock price moves of different stocks reveal which sectors and companies will be better off in the future than others."

The COVID-19 pandemic constitutes a 'natural experiment' that provides scholars in social science with a rare and unexplored opportunity to study a range of novel and interesting questions. Our present paper addresses a few among them. Indeed, among the three latest biggest stock market crashes, the COVID-19 pandemic was the one that had the quickest and deepest fall in a very short time, of less than a month, as well as the fastest and sharpest recovery to the pre-crash peak levels, in about two months – see Table 1 and Figure 1.

[Table 1 and Figure 1 about here]

Table 1 reveals and Figure 1 illustrates how the three latest biggest financial crashes compare among themselves. We have used NASDAQ data rather than S&P500 data since FRED availability by work days goes further into the past. As one can see, the historical trend is to pass from long-lasting crashes to short-lasting ones. The Dotcom crash lasted for 673 work days from pre-crash peak to trough, and then for another 3271 days until recovering just above the pre-crash index value. It thus persisted for nearly 13 years, and was characterized by the highest loss of index value between peak and trough of 77.94%, or

0.12% on average per work day during the fall. The Global Financial Crisis (GFC) crash lasted for 427 work days from peak to trough, and then for another 482 days until recovery. It thus endured for about 3 years and a half, and was characterized by a smaller loss of index value compared to the Dotcom crash between peak and trough, of 53.35%, but again 0.12% on average per work day during the fall. The COVID-19 pandemic crash features the smallest loss of stock index value in this comparison, 29.92%, but also the quickest and sharpest plunge, of 1.36% lost per day on average over 22 work days, as well as the quickest and sharpest recovery, of 56 days. The comparative perspective in Table 1 and Figure 1 singles out the uniqueness of the impact of the COVID-19 pandemic on stock markets in the US – but the picture across countries looks very similar.

[Figure 2 about here]

To see this impact more clearly, Figure 2 visualizes it in a plot where the new cases of COVID-19 in the US are measured on the left-hand side axis and the movements of the S&P500 stock index on the right-hand side axis. There are six (uneven) waves, or peaks, in the cases, and one huge plunge of the index at the start of the pandemic. Henceforth, relatively prolonged drops in share prices are frequent, and seem to be most of the time either nearly coinciding or coming somewhat later than the peaks in COVID-19 cases. Of course, this is only a first glance over the big picture. We shall delve into the disaggregation of the national stock indexes in our sample of 11 major world economies into 11 sectoral indexes, trying to figure out common patterns as well as specificities in diversity or heterogeneity. Such is the main goal of our present study.

We collected daily data on share prices by sector in an attempt to uncover empirically the dominant correlation patterns, given the changing perceptions of the public health crisis, and causality lags between the reported cases of contagion with COVID-19 and the movements of stock price indexes by sector and by country. This data set was coupled with a methodological approach that allows us to exploit its richness, namely a recent variant of a GARCH-based estimation due to Gibson *et al.* (2017) that handles well the curse of dimensionality. Such a combination led to the identification of many stylized facts about the consequences of the COVID-19 pandemic on sectoral stock indexes via human fear, initially quite desperate and unprotected, but subsequently dispersed gradually by the lockdowns, the vaccines, and the vaccination policies implemented almost everywhere in the world (with many specificities in the compulsiveness or intensity of the public health measures, it is true).

We, aiming essentially at a 'first pass' and a 'wide brush' here in this paper, split our daily sample into four equal subsamples, each lasting for half a year and corresponding, roughly, to the following stages in the development of policy responses to the spread of the pandemic:

1. 1st subsample period, or *1st half of 2020*, 1 January 2020 – 30 June 2020: outbreak of the COVID-19 pandemic in the world (beyond China) and first wave of national

lockdowns, plus initial monetary and fiscal policy measures enacted in addition to other government policies;

2. 2nd subsample period, or *2nd half of 2020*, 1 July 2020 – 31 December 2020: some summer-time easing of national lockdowns followed by a second wave of lockdowns and the news, in November, about the discovery of vaccines;

3. 3rd subsample period, or *1st half of 2021*, 1 January 2021 – 30 June 2021: beginning of national vaccination campaigns, 1st dose, mostly;

4. 4th subsample period, or *2nd half of 2021*, 1 July 2021 – 31 December 2021: completion of 2nd dose of vaccination in most countries and beginning of a booster (3rd vaccine) campaign in many of them.

These four subsample periods reflect a gradual, but fluctuating – as new dangers from new variants of the virus were also emerging, causing recurrent waves in the new cases of contagion – mitigation of the huge initial aggregate uncertainty and accompanying panic from the pandemic and a corresponding transition (rather than a sudden switch) into absence of fear. Furthermore, the economy was recovering by the end of our sample period of two years, moving to operate closer and closer to capacity, and people were gradually returning more and more to work, with supply chains being restored to a large extent (if not yet completely). There are nowadays several COVID-19 vaccines validated for use by the World Health Organization (WHO) and given Emergency Use Listing (EUL).[1] The first mass vaccination programme started in early December 2020 and the number of vaccination doses administered is updated on a daily basis on the COVID-19 dashboard of the WHO website.

Our paper is the first to document a number of novel empirical findings on the correlation and causality between the COVID-19 cases by country and the share prices by sector in 11 countries (accounting for 83.1% of global stock market capitalization), for which we managed to obtain a complete data set according to the GICS classification.[2] Some of our findings are quite general, and taken *en gros*; other are nuances and specificities established in the different countries or different sectors, reflecting particular anti-pandemic policies or other related events by country or sector.

[1] As of 12 January 2022, the following vaccines have obtained EUL, in chronological order and with dates listed as on the WHO website (see the end of this footnote): the Pfizer/BioNTech Comirnaty vaccine, 31 December 2020; the SII/COVISHIELD and AstraZeneca/AZD1222 vaccines, 16 February 2021; the Janssen/Ad26.COV 2.S vaccine developed by Johnson & Johnson, 12 March 2021; the Moderna COVID-19 vaccine (mRNA 1273), 30 April 2021; the Sinopharm COVID-19 vaccine, 7 May 2021; the Sinovac-CoronaVac vaccine, 1 June 2021; the Bharat Biotech BBV152 COVAXIN vaccine, 3 November 2021; the Covovax (NVX-CoV2373) vaccine, 17 December 2021; the Nuvaxovid (NVX-CoV2373) vaccine, 20 December 2021. Source: WHO, https://covid19.who.int

[2] The Global Industry Classification Standard (GICS) is an industry taxonomy developed in 1999 by Morgan Stanley Capital International (MSCI) and Standard & Poor's (S&P). The GICS structure consists of 11 sectors (listed and analyzed later on), 24 industry groups, 69 industries and 158 sub-industries into which S&P has categorized all major public companies. The system is similar to the Industry Classification Benchmark (ICB) maintained by FTSE Group.

To preview our most general empirical results from our rich data-informed investigation, we could state the following.

1. We document a shift of density mass from dominantly negative correlations by sector from the first and second halves of 2020, with no vaccines to reassure human fear, to dominantly positive correlations in the first and second halves of 2021, with the population vaccinated two and three times and recovering its optimism. The COVID-19 pandemic and the ensuing fear of its potential death toll or economic devastation erupted in huge aggregate uncertainty across the globe. It logically led to an initial rapid plunge of share prices in all examined countries and sectors. We capture this by dominantly (uncovered by kernel densities in the four subperiods we split our sample in) negative correlations between the COVID-19 cases and the stock price indexes by sector in all countries in most of 2020.

2. Granger causality tests further reveal almost immediate news transmission from the COVID-19 cases to sectoral price indexes, with some common patterns but also some heterogeneity by sector and country. The transmission lag from the new COVID-19 cases to sectoral share prices commonly varies from a lag of 1 day to a lag of 10 days, yet it is rather rare to have a single lag of Granger causality that is statistically significant at the 10% level and below; typically, there are 4-5 to, sometimes, 7-8 lags that are statistically significant in terms of our pairwise Granger causality tests. In such cases we have also identified the minimum p-value lag.

We interpret the documented main trends and findings by the usual narrative of social learning under the threat of an unexperienced contagious disease and no cure for the virus initially. People panicked all over the world in 2020, influencing dominantly in a negative direction share prices. By contrast, once equipped with vaccines and feeling reassured for the longer run, optimism recovered, and stock prices by sector too – with fluctuations and sectoral or country differences also documented, in addition to the common patterns. This has led to dominantly positive correlations from the middle of the sample onwards (roughly, coinciding with the news about vaccine discovery) for almost all stock exchange sectors and almost all countries in our sample in the last half of 2021.

We now give an overview of the scarce closest literature, focusing on that by sector, we have been able to identify. Using the GICS, Ramelli and Wagner (2020) look into the cross-section of returns and find that "investors (and analysts) became concerned about high corporate debt and about the survival chances of firms with little cash" (p. 652). They also reiterate that "while cash holdings are expensive for companies in general (in terms of opportunity costs, and due to the potential for agency problems), the emergence of this pandemic highlights the importance of precautionary cash holdings for firm value." Ramelli and Wagner (2020) divide their (much earlier than ours) daily sample into 3 subperiods, namely: 'Incubation', 2-17 January 2020; 'Outbreak', 20 January – 21 February 2020; and 'Fever', 24 February – 20 March 2020.

Furthermore these authors stress the following key findings by sector:

> "Over the whole period, the Telecom industry did relatively well, as the demand for services supporting work at home has skyrocketed. Pharma & Biotech and Semiconductors also performed relatively well, especially in the Fever period. Food and Staples Retailing performed negatively in the Incubation and Outbreak period, but surged in the Fever period, a striking indication that a broader crisis was anticipated by the market.
>
> Utilities gained strongly in Incubation and Outbreak, arguably because these firms, being overwhelmingly domestic, do not rely much on global markets, and the demand for their products was seen not to be much affected by the virus. However, in the Fever period, as investors sold all stocks as the worry of a U.S. recession grew bigger, these low-beta stocks underperformed.
>
> Over the whole period, Energy, Consumer Services, and Real Estate suffered particularly. Again, the time pattern is striking. Consumer Services and Real Estate performed neutrally in Incubation and Outbreak, but severely dropped in Fever as the health crisis in the United States grew. The Energy sector consists of many oil companies, which would suffer in a recession. The oil price shock is likely to have additionally hurt these companies, but they already underperformed strongly in the Incubation and Outbreak periods, as well as in the first half of the Fever period.
>
> The between-industry differences observed in the Fever period intuitively reflect differential degrees of disruption in firms' operations caused by social distancing and lockdown measures. This intuition is confirmed in the detailed analysis by Pagano, Wagner, and Zechner (2020). Using measures of the extent to which job activities in different sectors can be carried out from home and without human interaction in physical proximity (Dingel and Neiman 2020; Hensvik, Le Barbanchon, and Rathelot 2020; Koren and Peto 2020), they find that industries more affected in this dimension performed more poorly."

Following up on (the discussion paper version of) Ramelli and Wagner (2020), Griffith *et al.* (2020) was an early attempt to study the impact of COVID-19 on share prices in the UK by sector. Their policy note remains brief, and identifies % changes in share prices by sector in the London Stock Exchange relative to the FTSE-All Share Index over the period 2 January – 23 March 2020.

Capelle-Blancard and Desroziers (2020) write in a VoxEU note (of 19 June) that there is some evidence of shareholders having favored the less vulnerable firms during the first few months of the COVID-19 stock market crash. Further, they find that credit facilities, government guarantees, lower policy rates, and lockdown measures have mitigated the initial plunge in share prices the pandemic caused. However, these authors argue that fundamentals can only explain a small part of the stock market variations, focusing on the country level but abstracting from sectoral analysis.

Baker *et al.* (2020) use text-based methods back to 1900 in daily data and find that past pandemics have only mildly affected the US stock market. They explain the unprecedented market reaction at the advent of COVID-19 by government restrictions on commercial activity and voluntary social distancing, operating with powerful effects in the modern service-based economy. Similarly, Eachempati *et al.* (2021) exploit machine learning and Twitter to perform sentiment analysis on four stock exchanges, in the US (S&P500), the UK (London), China (Shanghai) and India (National). They find that the lowering of COVID-19 infected cases has led to the recovery of financial markets before vaccines were developed for the virus. They, however, do not disaggregate by sector either. Further and more recently, Hvid and Kristiansen (2020) examine the link between news sentiment measures and stock prices and find clear effects in the 10 MSCI sectors examined. They also identify and interpret differences across sectors, concluding that news sentiment has heterogenous effects on the stock market by sector, especially on the financial companies.

In another related recent paper, Kusumahadi and Permana (2021) examine the impact of COVID-19 on stock return volatility in 15 major economies, but do not disaggregate by sector. Using daily data spreading into the first half a year of the contagion worldwide, namely from January 2019 to June 2020, they find that changes in exchange rates have negatively affected stock returns in most countries. Identifying structural changes over the observation period, threshold generalized autoregressive conditional heteroskedasticity regressions are employed. These authors report evidence that the emergence of COVID-19 affected positively stock return volatility in all observed countries except the UK, but the magnitude of this effect is small.

Hansal *et al.* (2021) design a survey and focus on the COVID-19 stock market crash on household expectations. They provide correlational and experimental evidence how beliefs about the duration of the stock market recovery shape households expectations about their own wealth, planned investment and labor market activity. Klose *et al.* (2021) provide empirical analysis of the responses of European financial markets to the monetary and fiscal stimulus that was launched to mitigate the consequences of the pandemic. They do not look into sectoral disaggregation but compare yields from equities with yields from bonds in EU27 plus the UK and Switzerland. Goldstein *et al.* (2021) summarize the early research findings in a COVID-19 special issue. Some other studies have just looked at a single country, even if in (some) disaggregation.

The rest of the paper is structured as follows. Section 2 presents our data set and methodological approach. The results of our GARCH-based volatility estimation of the daily correlations between the COVID-19 cases and all 11 GICS sectoral stock price indexes in the 11 countries of our sample are documented and interpreted in section 3. Section 4 concludes, while further details on the data and the estimation results and illustrations by country and sector are provided in the supplementary online appendix (our data and code are available upon request as a zip archive).

2 Data and Methodology

2.1 Data

The selection of 11 countries in our sample is based on their size and role in the global financial, trade and economic system. They consist of the G7 members[3] and four other major economies.[4] The market capitalization of these 11 countries as of 2021 was more than USD 88.3 trillion or 83.1% of the global stock market capitalization.

The data consist of daily observations from 1st January 2020 to 31st December 2021, excluding the weekends and official holidays. The variable of registered COVID-19 cases is sourced from the WHO database. Except for the latter variable, all other variables are extracted from Refinitiv (Thomson Reuters) and have their values as the closing for the day. The "control" variables are five for each country, and standard in similar work: bitcoin, Brent oil, and gold prices, the daily exchange rate of each country's currency against the USD, while for the US it is the exchange rate of the USD against the EUR, and the 3-months sovereign bonds yield, which is for local currency bonds. All 11 GICS sectoral indexes are used, consisting of the following sectors: technology; telecommunications; health care; financials; consumer products and services; consumer staples; industrials; basic materials; energy; utilities; and real estate.[5] Where countries have more than one stock exchange, the stock exchange with the highest market capitalization was selected.[6]

The main research question of our study is to estimate empirically, by 'letting the daily data speak', the conditional correlation between the growth of COVID-19 cases and the growth of the sectoral indexes. We use the differences of the natural logs to obtain the growth rate. For the log transformation, we need to ensure positive values of the variables. This is the case for all variables, except for the number of COVID-19 cases, which are recorded as 0 by country before the pandemic erupted. To deal with the problem, we first identified the dates in 2020 from which the number of cases by country are all positive, i.e., there are continuously non-zero cases.[7] Similarly, in the data provided by the WHO, there are some days with zero cases after an elevated number of cases in the previous and before the following days.[8] In this case, we correct to ensure log compatibility of the number by averaging the previous and following days.

[3] Canada, France, Germany, Italy, Japan, the UK and the US.

[4] Australia, China, India and Spain.

[5] By contrast, Hvid and Kristiansen (2020) report data for 10 sectors (excluding real estate) and using a different methodology.

[6] In the US – Standard and Poor's 500, Australia – Standard and Poor's/Australian Stock Exchange 200, Canada - Standard and Poor's/Toronto Stock Exchange, China – Shanghai Stock Exchange, France – CAC 40, Germany – DAX, India – CNX Nifty, Italy – FTSE MIB, Japan – Tokyo Stock Exchange, Spain – IBEX 35, the UK – FTSE 100.

[7] For the US it is 26 February, Australia – 4 March, Canada – 5 March, China – 20 January, France – 26 February, Germany – 26 February, India – 3 March, Italy – 24 February, Japan – 14 February, Spain – 24 February and the UK – 2 March.

[8] This could be due to misreporting.

2.2 Methodology and Econometric Procedure

To investigate whether the volatility in COVID cases can explain the volatility of the different stock market sectoral indexes, daily time-varying conditional covariances and correlations are estimated and analyzed using a newly developed GARCH technique suggested by Gibson *et al.* (2017). This technique introduces a simple computational way for constructing large conditional covariance matrixes. The key motivation behind using the GARCH family of models here rather than other models is the ability of GARCH models to estimate the time-varying conditional variances that is considered the true measure of risk, and which is rarely similar to the constant unconditional variances estimated by other models (Morelli, 2002; Gibson *et al.*, 2017).

Traditionally, the BEKK-GARCH model (due to Baba *et al.*, 1987,[9] and Engel and Kroner, 1995) is considered the best Multivariate GARCH model in estimating the time-varying conditional variances for three reasons. Firstly, the BEKK-GARCH model ensures the positive semi-definiteness of the estimated conditional covariance matrixes by imposing a restriction implied automatically within the model structure compared with other Multivariate GARCH models such as the Vector-GARCH (VEC-GARCH) model, which does not ensure the positive semi-definiteness. Secondly, the BEKK-GARCH model allows for a more complex interaction between covariances which allows for more dynamics than other Multivariate GARCH models such as the Constant Conditional Correlation GARCH (CCC-GARCH) model, in which the time-varying conditional covariances are parametrized to be proportional to the product of the corresponding conditional standard deviations or the Dynamic Conditional Correlation GARCH (DCC-GARCH) model that imposes a constant dynamic structure for all conditional correlations. Finally, the BEKK-GARCH model allows for more time variation in covariances compared with other Multivariate GARCH model such as the Factor-GARCH (FGARCH) model, which not only limit the amount of time variation in covariances but also the number of the underlying factors for the variables being studied (Gibson *et al.*, 2017).

Having said that, one of the key problems of the BEKK-GARCH model is the dimensionality problem. As the number of included variables in a system increases, the model quickly generates a very large number of parameters. For a BEKK-GARCH (1,1) model, if the number of included variables in a system is N, the estimated number of parameters is equal to $2N^2 + \frac{N(N+1)}{2}$: see, among others, Caporin and McAleer (2010), and Gibson *et al.* (2017). As N increases, the number of parameters grows exponentially. For example, if the number of the included variables is equal to 17, the BEKK-GARCH (1,1) model requires to estimate 731 parameters in the variance equation, which is a very large number. Another problem with the BEKK-GARCH model is the nonlinearity in parameters, which makes its convergence very difficult for large N (Caporin and McAleer, 2010). To reduce these problems, two restrictions can be imposed, namely the diagonal or the scalar

[9] "BEKK" is an acronym originating in the first letters of the respective family names of the four coauthors of this discussion paper of 1987.

versions. However, these restrictions eliminate the interaction between the covariances and limit their time variation (Gibson *et al.*, 2017).

All of the above in mind, this newly suggested GARCH technique by Gibson *et al.* (2017) allows us to estimate larger conditional covariance matrixes, sidesteps the dimensionality problem of the traditional Multivariate GARCH family of models and drops all of the restrictions imposed by the pervious literature. This new technique rests on the following three simple equations (1)–(3), which explain the relationship between the conditional variance of any two variables, say x and y, and the conditional variance of the summation of those two variables as follows:

$$E\left(x_t + y_t \mid \Omega_t\right)^2 = E\left(x_t^2 \mid \Omega_t\right) + E\left(y_t^2 \mid \Omega_t\right) + 2E(x_t y_t \mid \Omega_t) \tag{1}$$

In conditional variance terms:

$$Var\left(x_t + y_t \mid \Omega_t\right) = Var\left(x_t \mid \Omega_t\right) + Var\left(y_t \mid \Omega_t\right) + 2Cov(x_t y_t \mid \Omega_t) \tag{2}$$

Hence:

$$Cov\left(x_t y_t \mid \Omega_t\right) = \frac{1}{2}\left[Var\left(x_t + y_t \mid \Omega_t\right) - Var\left(x_t \mid \Omega_t\right) - Var(y_t \mid \Omega_t)\right], \tag{3}$$

where, $Var\left(\cdot \mid \Omega_t\right)$ is the conditional variance of $(\cdot)$ and $Cov\left(\cdot \mid \Omega_t\right)$ is the conditional covariance of $(\cdot)$. The only assumption made here is that both x and y are zero-mean processes. Given these three equations, it is clear that in order to calculate the conditional covariance between any two variables, we need to estimate the conditional variance for each individual variable and the conditional variance for the summation of those two variables. These conditional variances simply can be estimated using a univariate GARCH (1,1) model for each single variable and for the summation of both variables.

Since the GARCH family of models uses the maximum likelihood to estimate conditional variances, each of the three estimated conditional variances mentioned above are expected to be consistent, and hence the calculated conditional covariance using equation (3) is expected to be consistent as well. However, by estimating these conditional variances using univariate GARCH models rather than Multiple GARCH ones, this could lead to an omitted variable bias problem due to omitting the covariance terms. Following Gibson *et al.* (2017) argument, it is true that the parameters of a univariate GARCH model are not consistent estimates for the parameter matrixes of Multiple GARCH ones. But it is not required here to have consistent estimate for the parameter matrixes of a Multiple GARCH model, we simply require a consistent estimate of the three conditional variances in equation (3). The consistency of these three conditional variances can be proved by the fact of the Wold Decomposition Theorem, which states that any process can be represented by an infinite order of a Moving Average univariate model. Given that the GARCH model is a time series representation of the variance process and the Wold Decomposition Theorem assumption of the existence of a valid univariate representation even if the underlying model is a multivariate one, a univariate GARCH (1,1) model which is equivalent to an infinite order of Moving Average model ensures the consistency of the conditional variances subject to including an adequate number of lags in the univariate GARCH model.

To apply this new approach, daily time-varying conditional variances for each of the 17 included variables (COVID-19 cases, the 11 GICS sectors, and our 5 "controls") and for the summation of the COVID-19 cases with each of the remaining 16 (except COVID-19 cases) variables are estimated using the standard GARCH model. Then, these GARCH models for each individual variable and each summation are used to construct their conditional variances. At this step, simply applying equation (3) gives us the conditional covariances. Following the academic financial literature, these univariate GARCH models are limited to the GARCH (1,1) specification. The mean equation for these univariate GARCH models takes the following error correction form:[10]

$$\Delta y_{it} = c_i + \sum_{i=1}^{17}\sum_{j=1}^{p}\delta_{ij}\Delta y_{it-j} + \sum_{i=1}^{17}\lambda_i y_{it-1} + \varepsilon_{it}, \qquad \varepsilon_t \mid I_{t-1} \sim N\left(0, h_t\right), \tag{4}$$

where Δy_{it} and Δy_{it-j} are the current and lagged return (growth rate) of the variable i, respectively. In addition, c is the deterministic component and p is the optimum lag length. Moreover, ε_{it} represents the current innovation of the variable i which is conditional on a previous information set I_{t-1} and is normally distributed with zero mean and h_t time-dependent variance. On the other hand, the variance equation for the GARCH models is specified as:[11]

$$h_{it} = \omega + \alpha\varepsilon_{it-1}^2 + \beta h_{it-1}, \qquad \omega > 0, |\alpha + \beta| < 1, \tag{5}$$

where h_{it} denotes the time-varying conditional variance of the variable i and ω is a constant which is restricted to be positive.[12] In addition, α and β are the coefficients of the lagged squared residuals ε_{it-1}^2 generated from the mean equation and the lagged conditional variance h_{it-1}, respectively. Given the conditional normality of residuals, these univariate GARCH models specified by equation (4) and (5) above, can be estimated by maximizing the following likelihood function:

$$\mathcal{L} = -\frac{T}{2}\ln\left(2\pi\right) - \frac{1}{2}\sum_{t=1}^{T}\ln|h_t| - \frac{1}{2}\sum_{t=1}^{T}\frac{\varepsilon_t^2}{\ln|h_t|}, \tag{6}$$

[10] The mean equation of univariate GARCH models for the summation terms is specified as follows:

$$\Delta y_{(x+i)t} = c_{x+i} + \sum_{i=1}^{17}\sum_{j=1}^{p}\delta_{ij}\Delta y_{it-j} + \sum_{i=1}^{17}\lambda_i y_{it-1} + \varepsilon_{(x+i)t}, \qquad \varepsilon_t \mid I_{t-1} \sim N\left(0, h_t\right),$$

where x is the natural logarithm of the daily COVID cases and i represents the natural logarithm of each of the remaining 16 variables.

[11] For the theoretical background of these univariate GARCH models, see Bollerslev (1986), Taylor (1987), Nelson (1991) and Glosten *et al.* (1993), among others.

[12] In the variance equation of univariate GARCH models for the summation terms, each h_i and ε_i will be replaced by $h_{(x+i)}$ and $\varepsilon_{(x+i)}$, respectively.

where T is the total number of observations and all other variables as defined earlier. The reason for using the absolute value for h_t in equation (6) is to ensure including positive conditional variances in this log-likelihood function.

As we discussed above, the univariate GARCH (1,1) model specified by equation (5) is estimated for each of the 17 included individual variables and for the summation of the COVID-19 cases with each of the remaining 16 variables.[13] Time-varying conditional variances are then generated using the univariate GARCH (1,1) model, which are found to satisfy three main conditions: (i) the model with an insignificant ARCH effect in residuals; (ii) the one that satisfies the stationarity condition; and (iii) the one that satisfies the variance non-negativity condition.

The results from testing statistically these three conditions are reported in tables 2 – 6 (left at the end of the main text for five of the considered major economies, namely, the US, the UK, Germany, Italy and Japan, to spare space and keep focus here) and in tables 1-6 in the appendix (for the remaining six countries, namely, Canada, Australia, France, Spain, China and India). As can be verified in these tables, our results from the univariate GARCH estimation are statistically significant most of the time, which allows interpreting them credibly, as we do in the next section. Taking up the US case in Table 2 to briefly comment and illustrate, we can see that all of the estimated GARCH (1,1) equations for both individual variables and summation terms have satisfied the above three conditions. For example, the non-negativity condition has been met for all equations with $\omega > 0$. Moreover, the coefficients of the lagged squared residuals generated from the mean equation and the lagged conditional variance all are found to be statistically significant either at 1% or 5% significance level. In addition, the stationarity condition $|\alpha + \beta|$ has been found to be met for almost all of them. Finally, it has been noticed that there is an insignificant ARCH effect in residuals with the majority of the equations are either statistically insignificant or significant at 10% significance level.

Depending on these generated time-varying conditional variances, the time-varying conditional covariances between the COVID-19 cases and the growth rate (return) of each of the subindexes are calculated using equation (3). Given the fact that covariances can tell us about the direction of the relationship between any two variables, and following the literature, the time-varying conditional correlations are finally also calculated, to eliminate the scaling problem of the conditional covariances and to make the interpretation of our results much easier.[14]

[13] The error term in all mean equations becomes a white noise once using a single optimum lag length.

[14] As standard, the time-varying conditional correlation is calculated here by dividing the time-varying conditional covariance between any two variables by the product of the time-varying conditional standard deviations of both variables.

3 Results and Interpretation

To motivate further our work, we present in Figure 3 a comprehensive view of our sample of 11 countries, each plotted in a panel with the number of its COVID-19 cases (blue narrow bars measured on the left-axis scale) per working day (i.e., we exclude weekends and official holidays when stock exchanges are closed) from 1 January 2020 through 31 December 2021 (plotted by work day count on the x-axis of each panel), i.e., a full picture of the two global COVID-19 pandemic years (so far). To get an idea of daily share price movements, we add in each panel the considered national stock index fluctuations (red curve measured on the right-axis scale).

[Figure 3 about here]

Figure 3 seems very useful to summarize the 'big picture'. It reveals some common patterns across countries, as well as country differences or specificities. It may also serve to visualize three potential country groups within our sample, corresponding to the rows of panels in Figure 3: the top row lists four countries with common language and similar history, culture and institutions, to which we could refer to as the 'Anglo-Saxon' or 'British Commonwealth' group; the middle row contains the four major EU economies; and the third row adds three of the most populous and important Asian economies. The common, or dominant patterns, that we think are worth highlighting in Figure 3 across our sample as a whole are as follows:

1. In all countries (except China and Australia) COVID-19 cases evolved in volatile cycles, or big waves, with at least 4 or 5 peaks per country and a highest level (except in China, Japan and India) at the end of the sample period, 31 December 2021.

2. In all countries the national stock market share prices (in this figure – but, similarly, the stock indexes in all 11 disaggregated sectors of the GICS, as can be seen in the figures by country coming a bit later) plunged nearly synchronously about late March 2020.

3. In all countries (except Spain, and – to a smaller extent – the UK, Australia, and Italy), the total market stock index (and often most other sectoral share prices in the figures by country, to be discussed soon) recovered relatively fast (compared to earlier stock market crashes) and reached higher levels (much higher in the US, Italy, France, Canada and India) at the end of the sample (compared to those just before the COVID-19 pandemic crash in March 2020), but with high volatility.

Against the background of these largely common and nearly synchronous general trends and common patterns, we addressed the question whether the volatility of COVID-19 cases and sectoral stock market indexes per country tends to be correlated, and if there is evidence on causality too. In search of an answer and letting the daily data speak, we implemented the recent GARCH-based econometric methodology in Gibson *et al.* (2017) to the data set described in the preceding section. The present section aims to outline and interpret our key findings.

3.1 Daily Correlations between COVID-19 Cases and Stock Prices by Country and Sector

In a first – and, we admit – very general and macro-finance level of our analysis, we find it most intuitive, as well as visual and insightful, to summarize our results in standardized graphs per country. Here in the main text of the paper, we look at five of the largest or mostly affected by the COVID-19 pandemic economies, while the remaining six countries are relegated to our supplementary appendix.

Our figures illustrate two dimensions, each of them by country. First, we plot the daily dynamics of the estimated correlation between the volatility of COVID-19 cases and the volatility of stock price indexes by sector in each country over the whole sample, i.e., for all working days of two full calendar years, 2020 and 2021. These figures – as will be discussed – show very volatile patterns, with the mentioned correlation staying negative for some periods and shifting to positive in other periods. Of course, these shifts are most likely driven by country-specific events at the high daily frequency we exploit here, but the purpose of our paper is to search, uncover and document some common patterns or stylized facts, *en gros* and broadly across our sample.[15] In a next step, we split the sample into four equal periods, indeed half-years, and summarize the density of the mentioned estimated daily correlations in kernel graphs. Looking into these kernel densities from the 1st half year through the 2nd and 3rd and into the 4th half year reveals a gradual shift of density mass from the negative (red) to the positive (green) region (half-kernel, in the graphs, split by the 0 vertical line), and we find this consistent with human behavior, as expected in general and as we discuss again a bit further below.

[Figures 4, 5 and 6 about here]

Taking as a benchmark the case of the US, what we document as our key findings and what we would suggest as key interpretations consists of the following. First, Figure 4 captures the plunge of all share price sectoral indexes in the 1st subsample period, with the advent of the COVID-19 pandemic. This is the initial negative effect of the new cases on stock prices, which – as we discussed in the introduction – operates via fear and panic under an unprecedented aggregate uncertainty when no cure has been yet found for the contagious and deadly disease, but abrupt measures of social distancing, lockdowns and work from home were implemented. One can, then, see this negative impact of COVID-19 cases

[15] Future work can, and should – of course – delve deeper and study these country-specific factors that influence the spread of information regarding COVID-19 cases, via the public health and policy responses, to stock prices, or other economic consequences of interest. We intend to take this – alternative and complementary – approach in a sequel paper.

alternating later on in some periods to positive, which may look strange. However, a closer look at the graphs, coupled with our ex-post knowledge of the events that unfolded in a similar fashion all over the world (but were hardly predictable at the outset), seems to make good sense. Once the death rate was revealed to be small, relative to past global pandemics, and work from home added to that in factories and offices where it was imminent (but with face masks and social distancing, minimizing contagion) kept on the global economy going, the initial fear and panic began gradually to disperse. As the first vaccines were announced by the end of the 2nd subsample, optimism resumed to recover, and with the huge stimulus by monetary, fiscal and other government policies, the share prices recovered too and went into historical peaks, yet with typical ups and downs. In our study, these developments show up in the 3rd subsample, when national mass vaccinations were implemented (1st and 2nd dose, mostly) and in the 4th subsample, where boosters (3rd dose) were implemented in addition and life started to return to normal more and more. One can observe that the correlations turn dominantly into positive by the end of our sample. The kernel densities by subperiod illustrate this major tendency convincingly: there is a clear shift of mass to the right (i.e., from red to green regions) in the kernel densities, for example comparing the 1st half-year period (with mostly bimodal shapes and dominant density mass on the left of the zero, in Figure 5) to the 4th half-year period (now with mostly unimodal shapes and dominant density mass on the right of the zero, in Figure 6). In terms of specificity by sector, the consumer staples, health, tech, utilities, and real estate sectors have switched into the positive areas most impressively, but all 11 sectors fit this general trend, even if less clearly.

In effect, our methodological approach has enabled us to infer empirically from the data and document the set of stylized facts or common patterns we have just outlined, based on the US benchmark. Our interpretation for the shift of sign from negative to positive of the volatility correlations extracted econometrically between COVID-19 cases and stock price sectoral indexes (in the US figures, here, and in the rest of our sample, hereafter), is related to the learning process for the global society when faced with something unexperienced and life-threatening, the current pandemic. While humans remained extremely vulnerable because no cure was at sight, pessimism translated into economic activity and stock markets, which crumbled down; once gradual improvement of the prospects to fight the pandemic were raising the optimism, and once protected by the vaccines (even if new variants were appearing), people restored confidence in the near future and swung back into stock market optimism, raising share prices in the US (here, in the US figures, and worldwide, in the rest of our sample). *En gros*, this is our key interpretation. Indeed, it makes good sense according to the related literature reviewed earlier.

[Figures 7, 8 and 9 about here]

Figures 7, 8 and 9 reveal the same key trends and patterns for the UK. The major evident finding in the UK data again is the shift of density mass from the negative to the positive region of the kernels by sector, as one moves from the first half of 2020 (Figure 8) to the 2nd half of 2021 (Figure 9). In the UK, the health, tech, and real estate sectors have witnessed the most significant shift from pessimism to optimism. Another UK specificity is the opposite trend for basics, energy and telecom.

[Figures 10, 11 and 12 about here]

Figures 10, 11 and 12 for Germany fit the commented dominant trend and pattern for the US and the UK. In fact, the German kernels appear even more convincing, with more density mass shifting from left to right over the four subsample periods for all sectors.

[Figures 13, 14 and 15 about here]

Italy (most convincingly of all five economies analyzed here in the main text) – see figures 13, 14 and 15 – and Japan (less so, but comparably to Germany) – see figures 16, 17 and 18 – confirm the same general conclusion and interpretation.

[Figures 16, 17 and 18 about here]

Analogous findings and key explanation apply to the figures for the remaining six countries in our sample that are relegated to the supplementary appendix. Of course, this "big picture" needs to be scrutinized more carefully, disentangling specificities by country and sector.

3.2 Speed of Transmission from COVID-19 Cases to Stock Prices by Country and Sector

As a next step, we employed our data set and estimation results to learn about the speed of the transmission of the effect from the new daily COVID-19 cases to the stock price indexes by sector in each country. To infer this speed of transmission from the data, we proceeded to Granger causality tests with lags ranging between 1 and 15 days for each country and sector. As a uniform threshold throughout, we take the 90% confidence level of statistical significance of these tests. As might be expected, our results documented significant heterogeneity, but we were also able to uncover important common patterns, which we discuss next.

[Table 7 about here]

Table 7 reports our Granger causality test p-values for all 11 GICS sectors in the US and the UK. These two countries display a lot of similarity in that:

1. The daily share price changes in all sectors are Granger-casused by the new COVID-19 cases with a rapid transmission of 3 days (except the UK energy sector where this transmission is even faster, 2 days).

2. The validity of Granger causality at the daily frequency remains for most sectors of the up to 15 lags we studied.

3. The only exception of the above conclusion in both economies is the tech sector, with transmission of 3 days in the UK (the only lag where the null hypothesis of Granger noncausality cannot be rejected at 5% or 10% significance level) and 5 days in the US (with 3 occasions in total of Granger causality at 10%).

The main difference between these two countries is that in the UK the transmission is sometimes delayed by a day (basic materials) or two (staples, health, telecom and utilities); whereas in the US the transmission to the energy sector is delayed by 3 days; the other sectors reveal the same speed of transmission.

[Table 8 about here]

Turning to Canada and Australia in Table 8, these two economies display fast transmission to most of their sectors: 2 days of delay from COVID-19 cases to stock prices in Canada for all sectors except basic materials and health; and a day of delay in Australia for finance, staples, health, telecom and utilities. In both countries, the validity of Granger causality is largely preserved to later lags, often going to 15 days, as was in the case of the US and the UK. We here see another reason to group these four economies in an 'Anglo-Saxon' or 'British Commonwealth' group.

[Table 9 about here]

Moving, next, to the two leading EU economies, Germany and France in Table 9 generally do not support conclusion 2. above, even if for the finance, basic materials and industrial sectors this is largely true again, but up to a shorter lag, of about 9 days. What is common to Germany and France is that in 3-4 of their sectors share prices are affected even faster than in the US and the UK, at lag 1. That is, we uncover that in Germany and France the news from the new COVID-19 cases has travelled faster, by one day, to affect share prices than in the US and the UK. Yet, a main difference between Germany and France stands out starkly for some sectors: in particular, staples, consumer products and energy share prices are affected by daily news on COVID-19 cases with a delay of 6 days in France relative to Germany; whereas in Germany health and utilities are affected with a similar delay of 7 days relative to France. Such specificity may be due to possible differences in the structure of the two economies, including the ability to work from home during lockdowns and other factors.

[Table 10 about here]

Passing next to the two other leading EU economies, Italy and Spain, we can establish a delay of another 2 days in the transmission from cases to share prices relative to the UK and the US, except for the health sector in Italy and the basic materials and energy sectors in Spain that experience a faster transmission, by a day, relative to the same benchmark in Table 7. In terms of the validity of the Granger causality over multiple lags, Italy and Spain are more similar to Germany and France and less similar to the US and the UK. A peculiarity in Italy is that we do not find Granger causality from new COVID-19 cases to stock prices in the consumer products sector: this is the only sector in all six considered economies so far where transmission from COVID-19 cases to share prices has not been captured by Granger causality (up to a lag of 15 days, to be more precise).

[Table 11 about here]

We, finally, turn to the four big Asian economies in our sample. Starting with China and Japan in Table 11, we can easily establish another stylized fact: namely, that the transmission from the new COVID-19 cases to stock prices is: (i) extremely delayed compared to the leading Western economies we already discussed, starting with a lag of 6 or 7 days in China and 10, 11, 12 or 13 days in Japan; (ii) and even non-existent (at least until a lag of 15 days) for five of the sectors in China (basic materials, staples, health, utilities, and real estate) and two in Japan (the last two mentioned before real estate for China). While the Chinese economy may not fit well a completely market economy definition with a dominant role of the stock exchange, the Japanese economy does fit such a characterization. This delayed transmission to, or reaction of, share prices, therefore, may have some deeper, historical and cultural roots, which we do not have purpose to explore in this paper, but leave for future research.

[Table 12 about here]

Looking, then, over the Granger causality results for India in Table 12, we can be surprised again, in the sense that this country reveals the opposite speed of transmission pattern compared to the one just stated for China and Japan. While still belonging to the Asian continent, stock prices in India react fast in four of the sectors, with a lag of 1, 2 or 3 days. Moreover, the Granger causality remains valid until (almost) lag of 15 days for (almost) all sectors.

[Table 13 about here]

To sum-up all these findings in the present subsection, we have prepared Table 13. Apart from some common patterns or specificities we already highlighted, we would conclude here by enumerating what we think are the main insights from the analysis of the speed of transmission from COVID-19 cases to share prices by sector. These seem to be the following.

1. In all 11 major world economies in our sample the volatility of share prices in four of all 11 GICS sectoral indexes covered has been the most responsive – across the board

– to the volatility in the new COVID cases: namely, the financial, energy, industrial and tech sectors.

2. In an opposite sense, the least responsive sectors – across the board – have been revealed to be three other ones: namely, consumer products and services, health and utilities sectors. In fact, it may be that some higher responsiveness may be exhibited beyond the maximum lag of 15 days we have checked in the present study. It could also well be that fluctuations in share prices in these three sectors are not Granger-caused by fluctuations in the daily COVID-19 cases for some structural, institutional or technological reasons, which further research could look into.

3. In-between, with some sort of intermediate responsiveness or speed of transmission, are the remaining four sectors: namely, basic materials, consumer staples, telecom, and real estate.

4. At least in one of the 11 countries, but often in (many) more, the volatility of the share prices in each sector is Granger-caused by the volatility in new COVID-19 cases immediately, i.e., at a lag of a single day. Moreover, in most of the countries for most of the sectors the established Granger causality persists up to a lag of (almost) 15 days.

All in all, we thus find convincing causal evidence that volatility in COVID-19 cases Granger-causes (almost) immediately – at a lag of 1, 2 or 3 days most of the time – volatility in share prices in all 11 sectors studied in (almost) all 11 major economies in our sample. This evidence, more broadly, documents the general as well as the differentiated impacts of an immense and rare public health disaster, or natural experiment, on stock prices by sector. The implied mechanism most likely operates, as we argued, via human fear or panic in a situation of aggregate uncertainty, death toll threat and reality, and corresponding waves of pessimism and optimism in the health of the macroeconomy globally and financial markets, naturally and ultimately affecting behavior, including in consumption, investment and stock markets.

4 Concluding Comments

This paper is the first to document a number of novel empirical findings on the correlation and causality between the COVID-19 cases by country and the share prices by sector, in 11 major countries and all 11 GICS sectors of the stock exchange. The most general empirical results from our rich data-informed investigation appear to be the following.

The COVID-19 pandemic and the ensuing fear of its potential death toll or economic devastation initially exploded in huge aggregate uncertainty across the globe. It logically led to a contemporaneous rapid plunge of share prices in all examined countries and sectors. We document this phenomenon by statistically significant and dominantly (uncovered by kernel densities in the four subperiods we split our sample in) negative correlations between the COVID-19 cases and the stock price indexes by sector in all countries in most of 2020. Further, the Granger tests we presented allowed a clear data-supported causal interpretation, with prevailing lags of about 2-3 to 5-6 days in such a news transmission speed. We documented as well that it is rather rare to have a single lag of Granger causality (statistically significant at the 10% level and below); typically there 4-5 to sometimes 7-8 lags that are statistically significant in terms of our pairwise Granger causality tests. In such cases we have also identified the minimum p-value lag.

Not surprisingly perhaps, this initial fear and sharp plunge in financial markets has been gradually, but hesitantly, recovering over the course of 2021. It definitely depended on the news of the vaccines and their implementation by public health policies of various degrees in the different countries of our sample, as well as on the subsequent waves of COVID-19 contagion sparkled by the mutations and variants of the original virus and their perceived danger to human life or the development of the disease. This has subsequently led to dominantly positive correlations after the middle of the sample onwards for almost all stock exchange sectors and almost all countries in our sample in the last half of 2021. What our estimation captures reflects the fact that the initial panic, uncertainty and fear gave way to gaining control over the COVID-19 spread, and a recovery of optimism in the prospects for the economy and financial markets as the initial contagion curves flattened out in most parts of the world since the summer of 2020.

Thus, the difference in the uncovered empirically dominant skewness of the kernels, to the left (negative/red values) in the first half of 2020 versus to the right (positive/green values) in the second half of 2021, is due to the fact that in the earlier period there were worsening economic conditions as a result of the lockdowns and the sudden stops in most economic activities. In addition, there were still no stimulus measures put in place and economic agents, with such a reduction in income, were keen to keep their assets in cash and other asset categories such as gold, rather than in the riskier equities. However, in the later period, the economic recovery, in tandem with the stimulus packages and vaccines distribution improved confidence and stimulated economic agents to seek back higher returns given the record low interest rates globally and the excessive amount of money disbursed with the easing of monetary and fiscal policies.

It goes without saying that our paper was intended, essentially, as a first pass and a broad brush, establishing a rich set of sectoral stylized facts in the field of study across a subset of major economies representing 83.1% of global stock market capitalization. Hence, our perspective here was, mostly, a macro-finance one. As such, it remains rough, perhaps blunt, and therefore limited in so far as refined details by country structure, institutions, culture and implemented policies are needed, as well as the country-relevant dates to identify news on both COVID-19 cases and share prices by sector in specific event studies. We leave many such questions – largely in the domain of asset pricing, corporate finance and news transmission and assimilation into stock prices or indexes – for future research, including our own.

References

[1] Baba, Y., Engle, R. Kraft, D., Kroner, K. (1987), "Multivariate Simultaneous Generalized ARCH," Discussion Paper, University of California, San Diego.

[2] Baker, S. R., Bloom, N., Davis, S. J., Kost, K., Sammon, M. and Viratyosin, T. (2020), "The Unprecedented Stock Market Reaction to COVID-19," *Review of Asset Pricing Studies* 10, 742–758.

[3] Bollerslev, T. (1986), "Generalised Autoregressive Conditional Heteroscedasticity," *Journal of Econometrics* 31, 307–327.

[4] Capelle-Blancard, G., Desroziers, A. (2020), "The Stock Market and the Economy: Insights from the COVID-19 Crisis," VOX, CEPR Policy Portal.

[5] Caporin, M., McAleer, M. (2010), "Do We Really Need Both BEKK and DCC? A Tale of Two Multivariate GARCH Models," KIER Discussion Paper, 738, Kyoto.

[6] Dingel, J. I., Neiman, B. (2020), "How Many Jobs Can Be Done at Home?" *Journal of Public Economics* 189,104–235.

[7] Eachempati, P. S., Praveen R., Panigrahi, P. K. (2021), "Sentiment Analysis of COVID-19 Pandemic on the Stock Market," *American Business Review* 24 (1), Article 8.

[8] Engle, R. F., Kroner, K. F. (1995), "Multivariate Simultaneous Generalized ARCH," *Econometric Theory* 11 (1), 122–150.

[9] Gibson, H. D., Hall, S. G., Tavlas, G. S. (2017), "A Suggestion for Constructing a Large Time-Varying Conditional Covariance Matrix," *Economics Letters* 156, 110–113.

[10] Glosten, L., Jagannanthan, R., Runkle, R. (1993), "On the Relationship between the Expected Value and the Volatility of the Nominal Excess Returns on Stocks," *Journal of Finance* 48(5), 1779–1801.

[11] Goldstein, I., Koijen, R. S. J., Mueller, H. M. (2021), "COVID-19 and Its Impact on Financial Markets and the Real Economy," *Review of Financial Studies* 34, 5135–5148.

[12] Griffith, R., Levell, P., Stroud, R. (2020), "The Impact of COVID-19 on Share Prices in the UK," Briefing Note, Institute for Fiscal Studies (27 Mar 2020).

[13] Hanspal, T., Weber, A., Wohlfart, J. (2020), "Exposure to the COVID-19 Stock Market Crash and Its Effect on Household Expectations," *Review of Economics and Statistics* 103 (5, December), 994–1010.

[14] Hassan, H. A. (2017), *An Empirical Study on the Optimal Monetary Policy and Financial Market Volatility in Egypt*, PhD Thesis, University of Leicester, UK.

[15] Hvid, A. K., Kristiansen, K. (2020), "How News Affects Sectoral Stock Prices through Earnings Expectations and Premia," European Central Bank Working Paper 2493 (November),

[16] Keynes, J. M. (1936), *The General Theory of Employment, Interest and Money.* Reprinted in Keynes, Collected Writings. Vol. 7.

[17] Klose, J., Tillmann, P. (2021), "COVID-19 and Financial Markets: A Panel Analysis for European Countries," *Journal of Economics and Statistics* 241 (3), 297–347.

[18] Koren, M., Peto, R. (2020), "Business Disruptions from Social Distancing," arXiv, preprint.

[19] Kusumahadi, T. A., Permana, F. C. (2021), "Impact of COVID-19 on Global Stock Market Volatility," *Journal of Economic Integration* 36 (1, March) 20–45.

[20] Mindell, J. (1961), "How News Affects Market Trends," *Financial Analysts Journal* 17(1), 31–34.

[21] Morelli, D. (2002), "The Relationship between Conditional Stock Market Volatility and Conditional Macroeconomic Volatility: Empirical Evidence Based on UK Data," *International Review of Financial Analysis* 11(1), 101–110.

[22] Nelson, D. B. (1991), "Conditional Heteroscedasticity in Asset Returns: A New Approach," *Econometrica* 59(2), 347–370.

[23] Pagano, M., Wagner, C., Zechner, J. (2020), "Disaster Resilience and Asset Prices," Working Paper, University of Naples Federico II.

[24] Ramelli, S., Wagner, A. F. (2020), "Feverish Stock Price Reactions to COVID-19," *Review of Corporate Finance Studies* 9 (3, November), 622–655.

[25] Wagner, A. F. (2020), "What the Stock Market Tells Us about the Post-COVID-19 World," *Nature Human Behavior* 4, 440.

[26] Walras, L. (1874–1877), *Eléments d'économie politique pure ou Théorie de la richesse sociale*, 2 parts, Lausanne: L. Corbaz; Paris: Guillaumin; Bâsle: H. Georg.

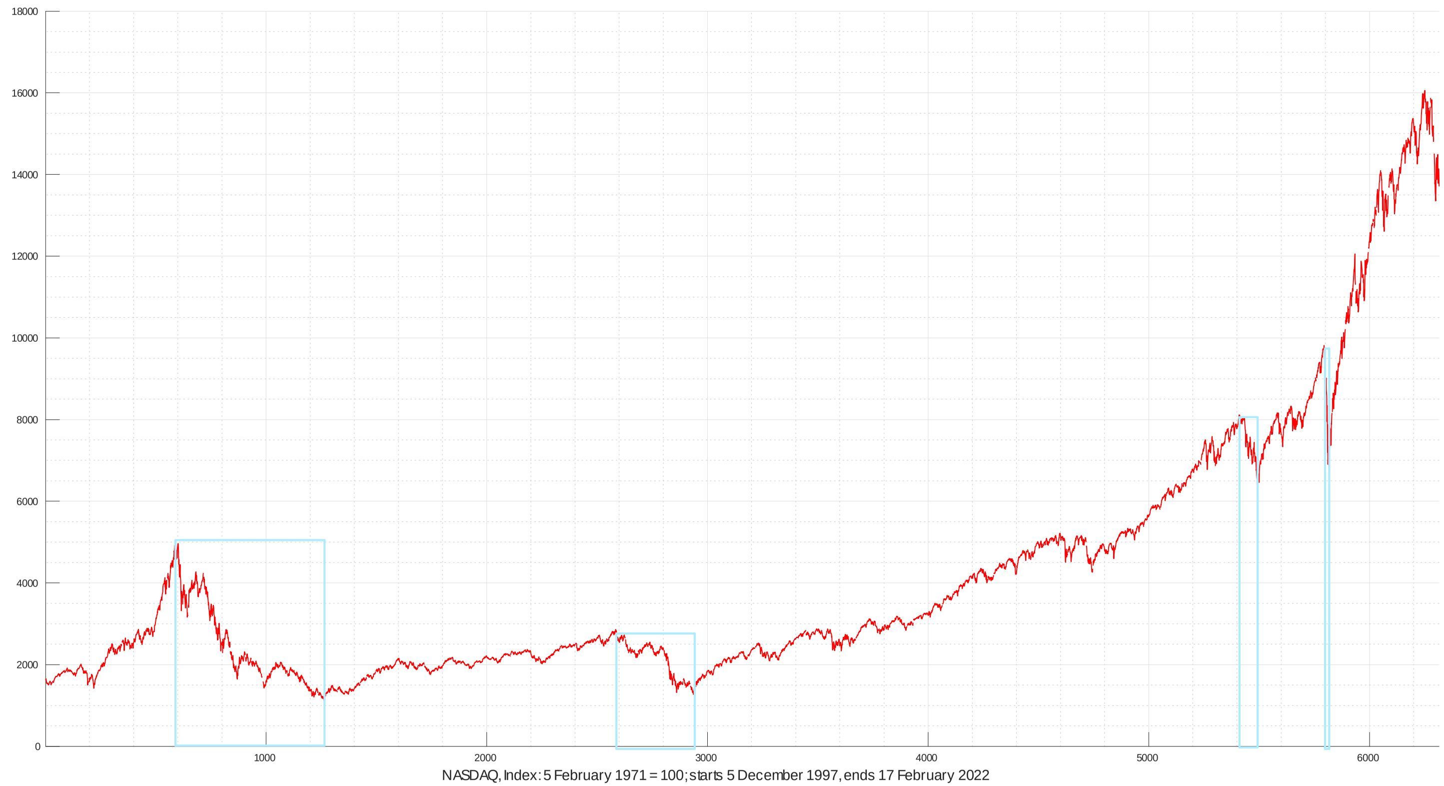

Figure 1: The Latest 3 Biggest Stock Market Crashes: NASDAQ Work Day Plot (x-axis) – Dotcom Crash (on the left), Global Financial Crisis Crash (in the centre), COVID-19 Pandemic Crash (on the far right), peak-to-through event windows in light blue (see also Table 1)

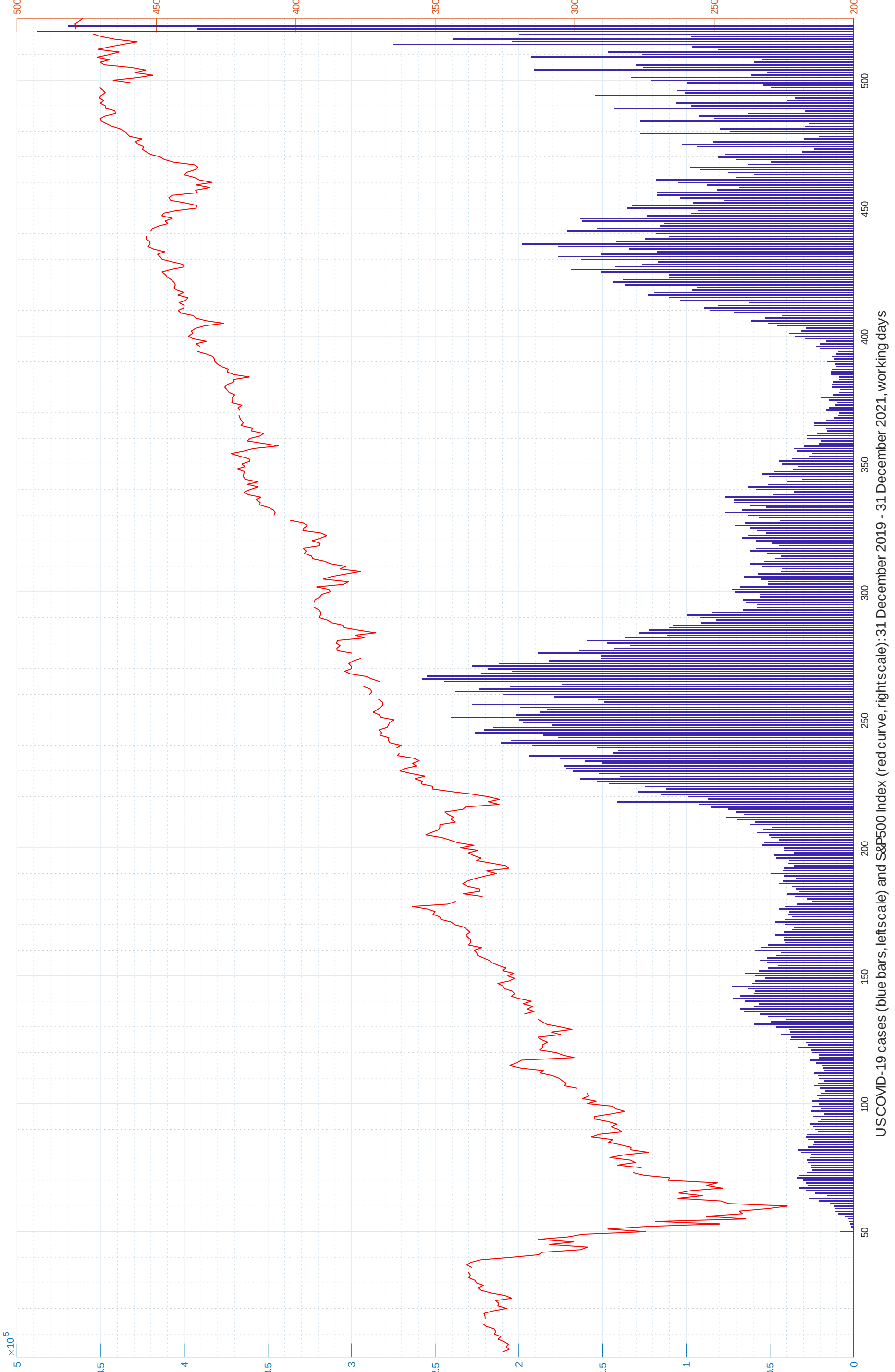

Figure 2: COVID-19 Cases and S&P500 Index, Work Day Plot

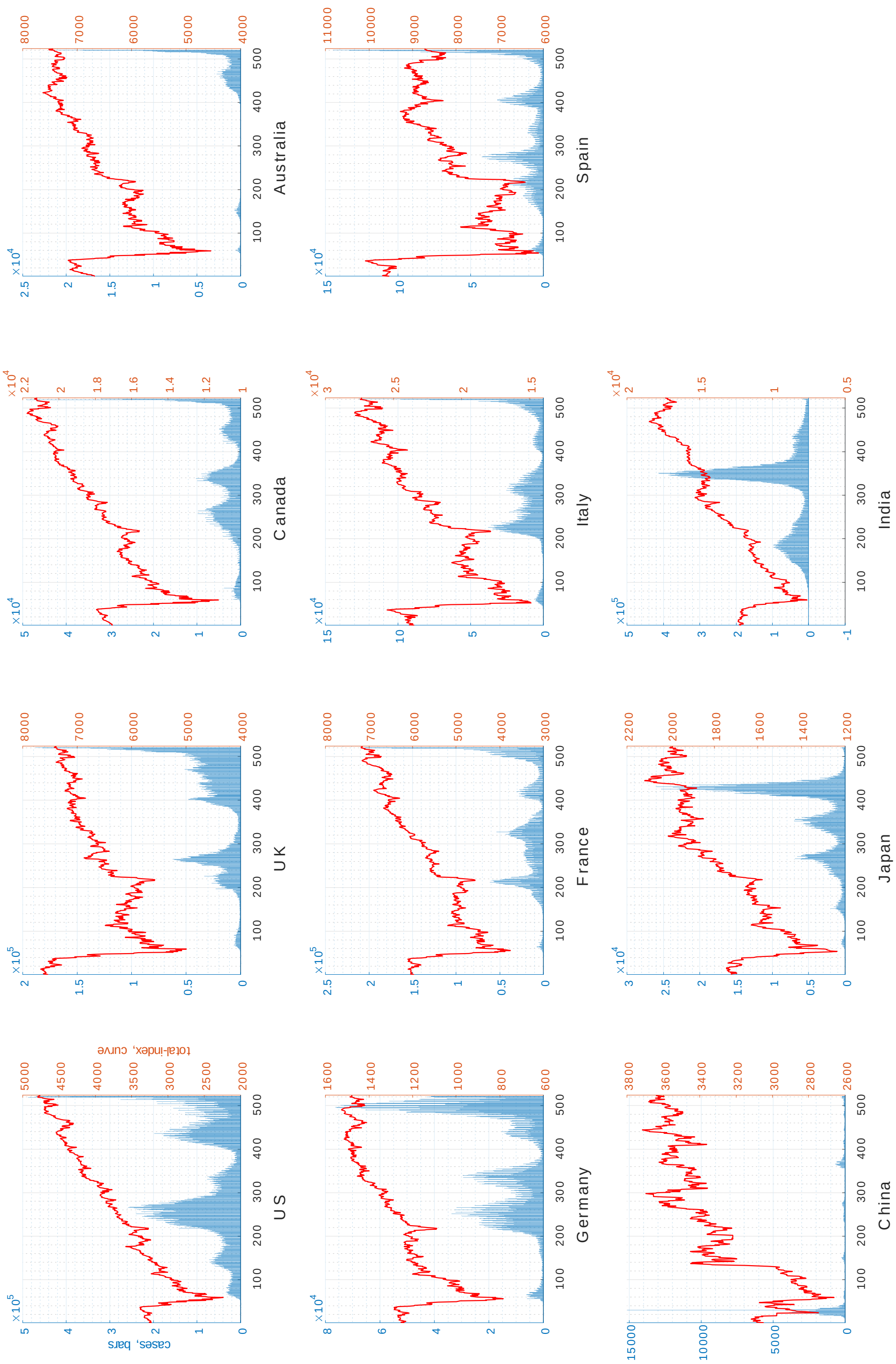

Figure 3: COVID-19 Cases and National Stock Market Indexes, Dynamics in 11 Economies, 2020-21

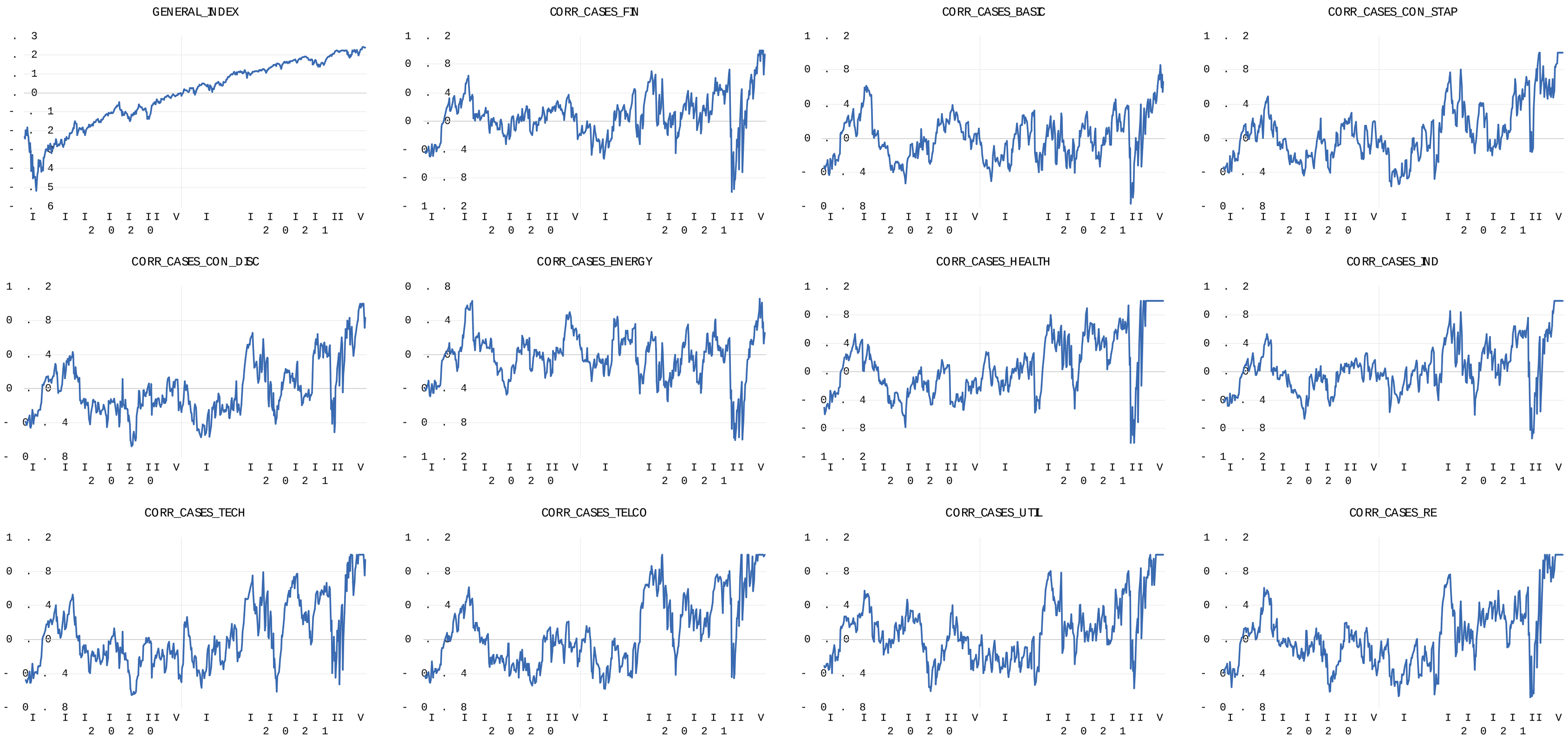

Figure 4: US – Estimated Daily Correlations between COVID-19 Cases and Sectoral Stock Price Indexes, Dynamics, 2020-2021. The top-left panel in this and all analogous figures that follow shows the work-day dynamics of the respective national stock price index referred to in footnote 6.

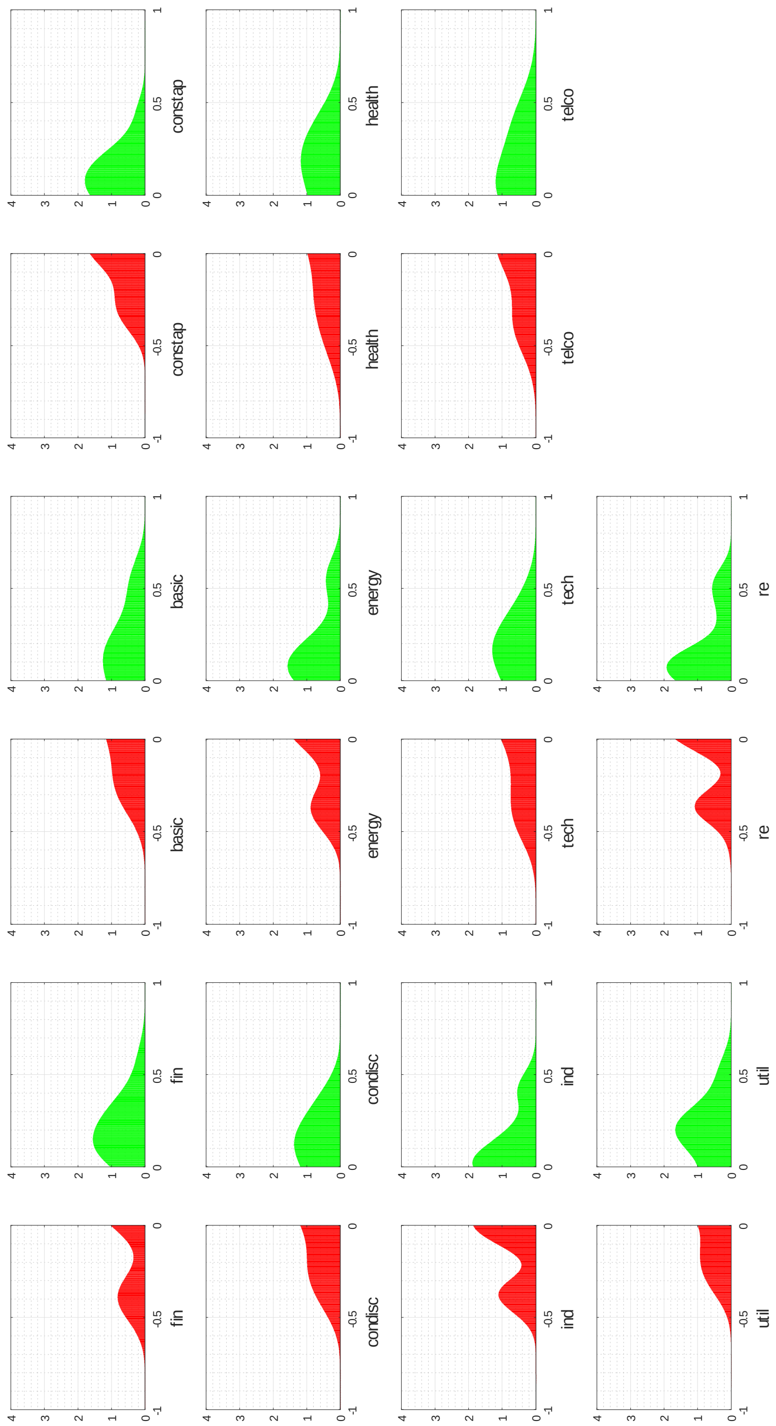

Figure 5: US – Estimated Daily Correlations between COVID-19 Cases and Sectoral Stock Price Indexes, Kernels, 2020, 1st half of the year

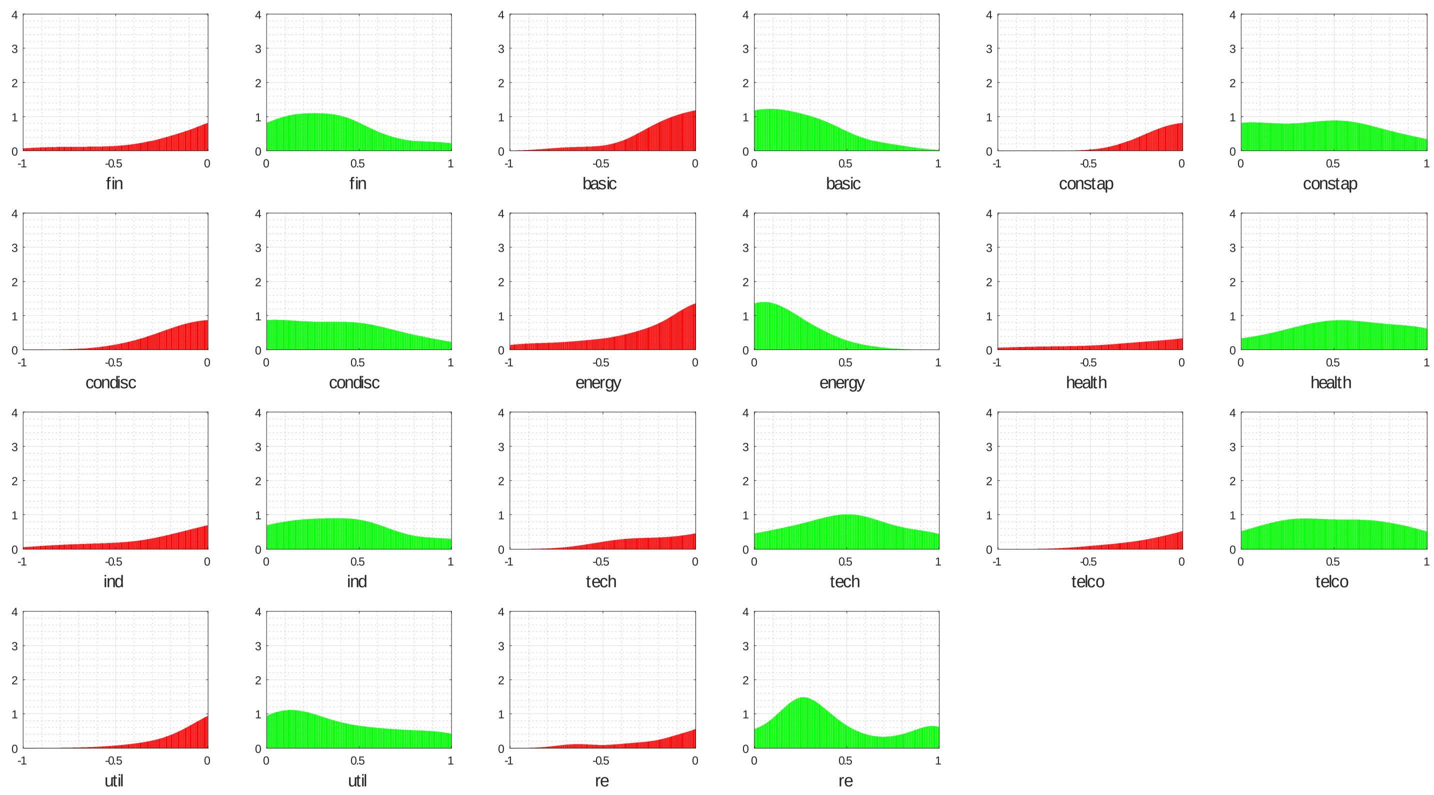

Figure 6: US – Estimated Daily Correlations between COVID-19 Cases and Sectoral Stock Price Indexes, Kernels, 2021, 2nd half of the year

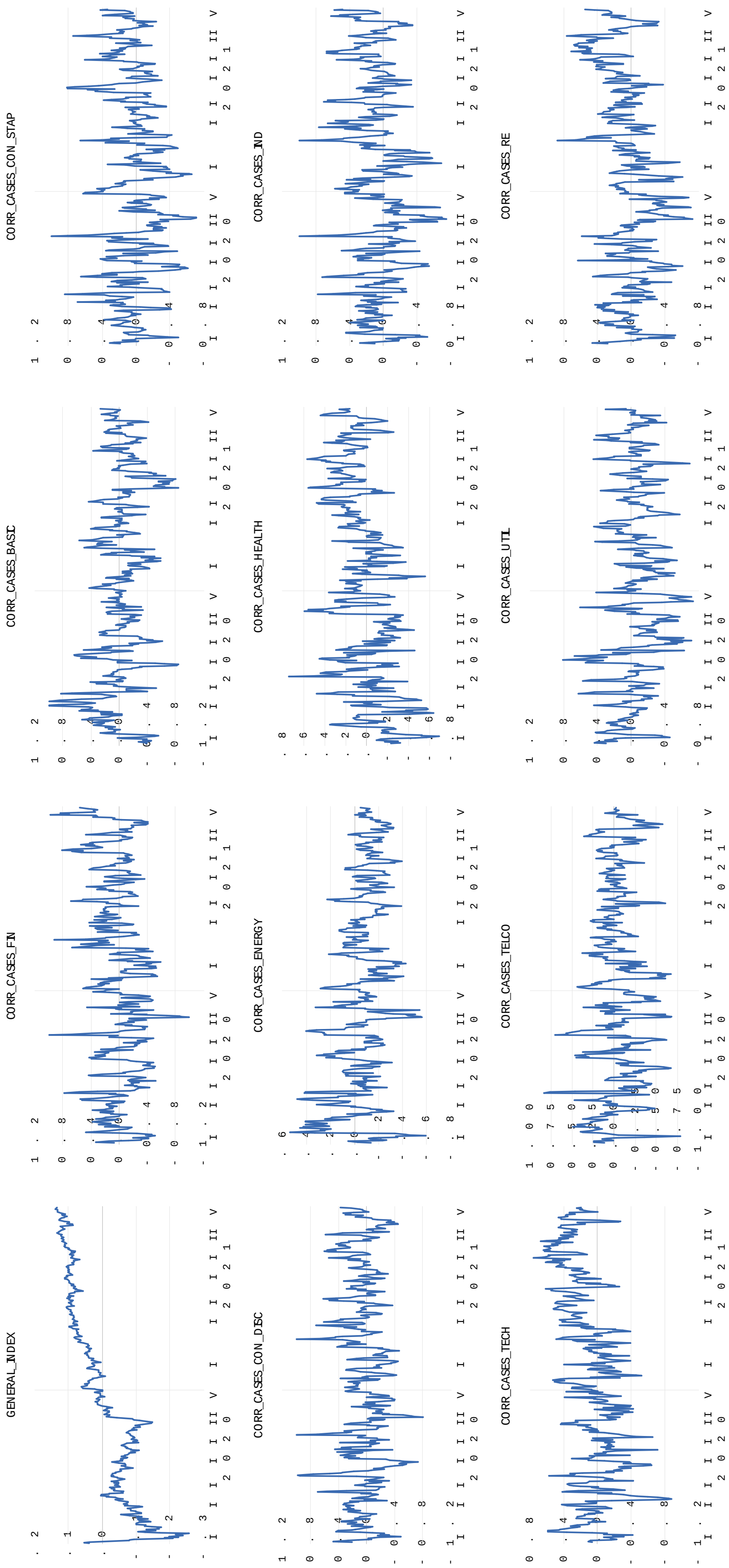

Figure 7: UK – Estimated Daily Correlations between COVID-19 Cases and Sectoral Stock Price Indexes, Dynamics, 2020-2021

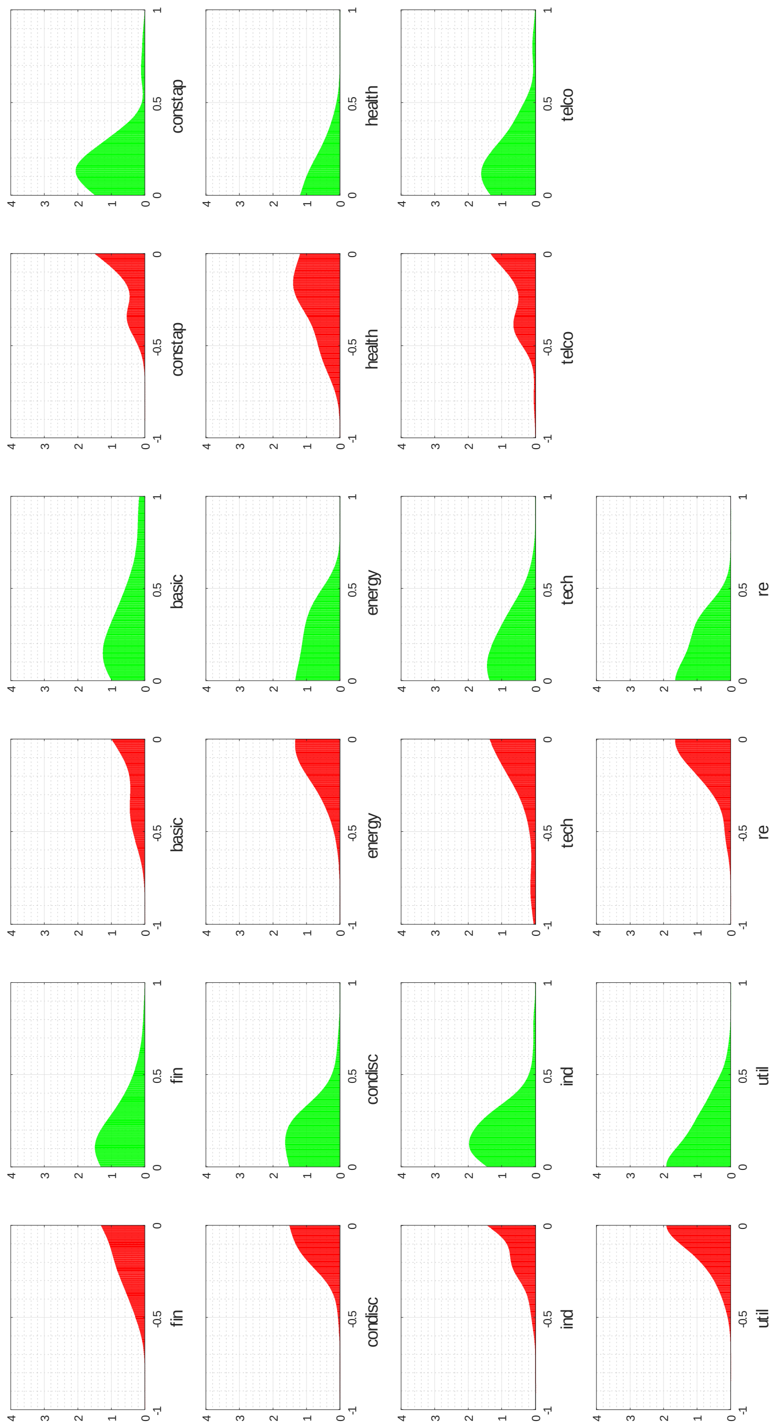

Figure 8: UK – Estimated Daily Correlations between COVID-19 Cases and Sectoral Stock Price Indexes, Kernels, 2020, 1st half of the year

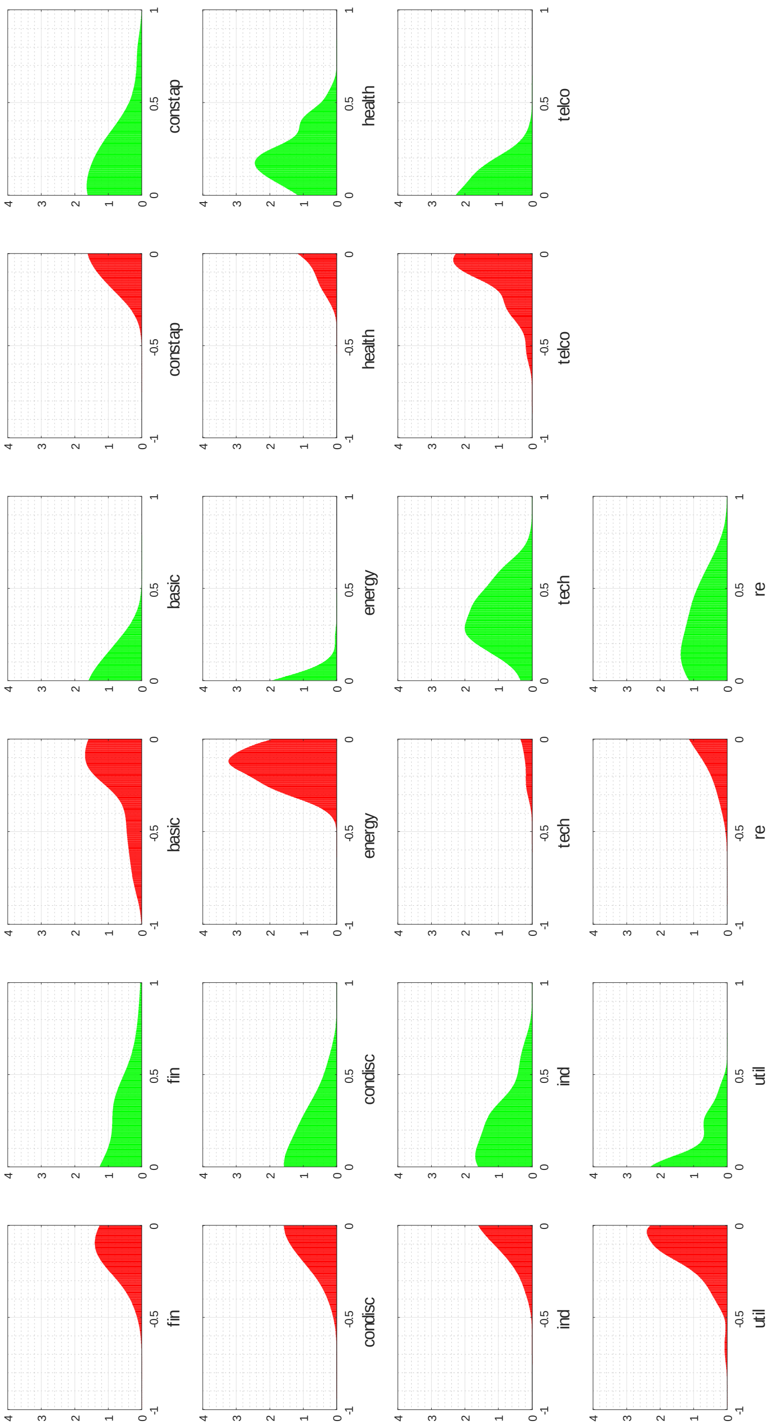

Figure 9: UK – Estimated Daily Correlations between COVID-19 Cases and Sectoral Stock Price Indexes, Kernels, 2021, 2nd half of the year

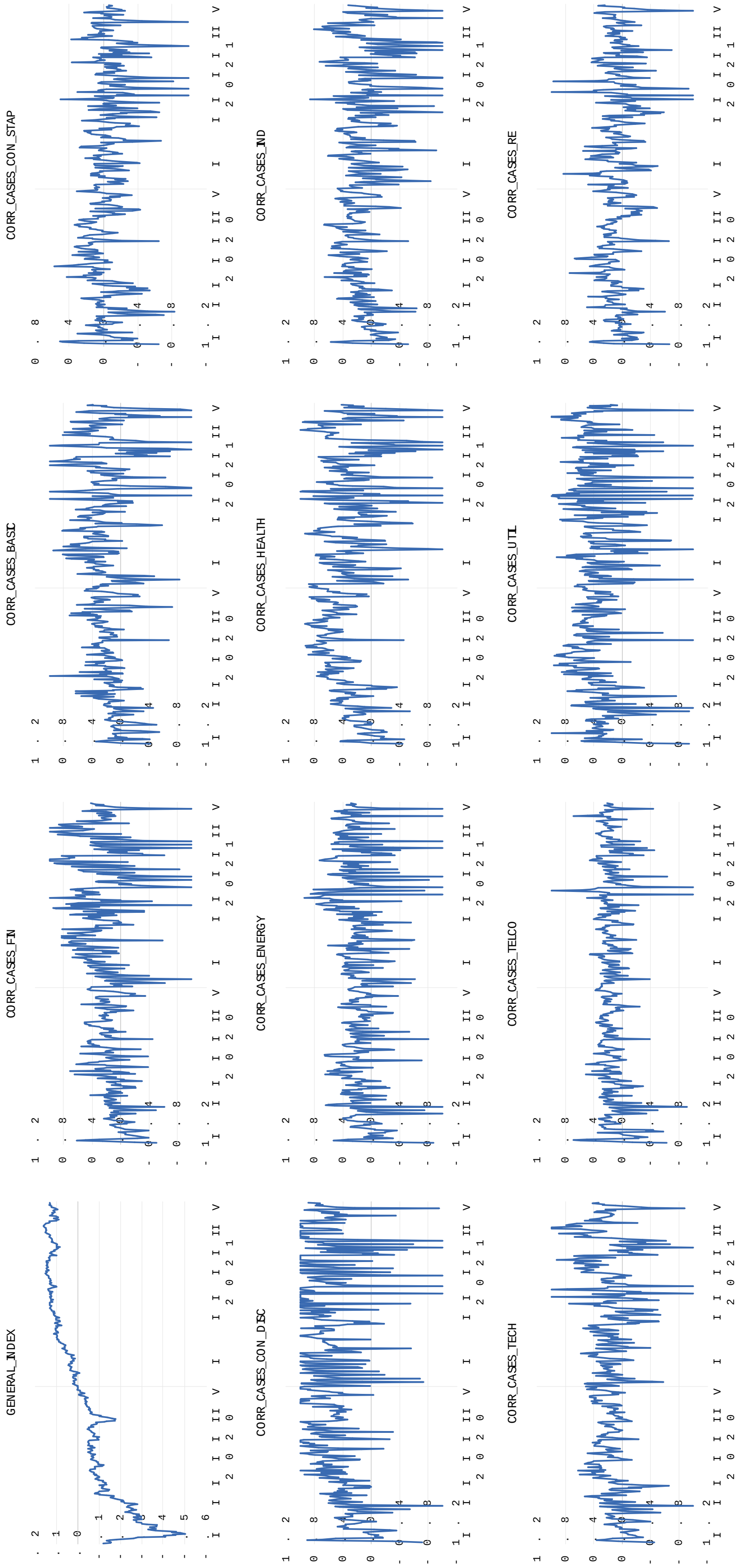

Figure 10: Germany – Estimated Daily Correlations between COVID-19 Cases and Sectoral Stock Price Indexes, Dynamics, 2020-2021

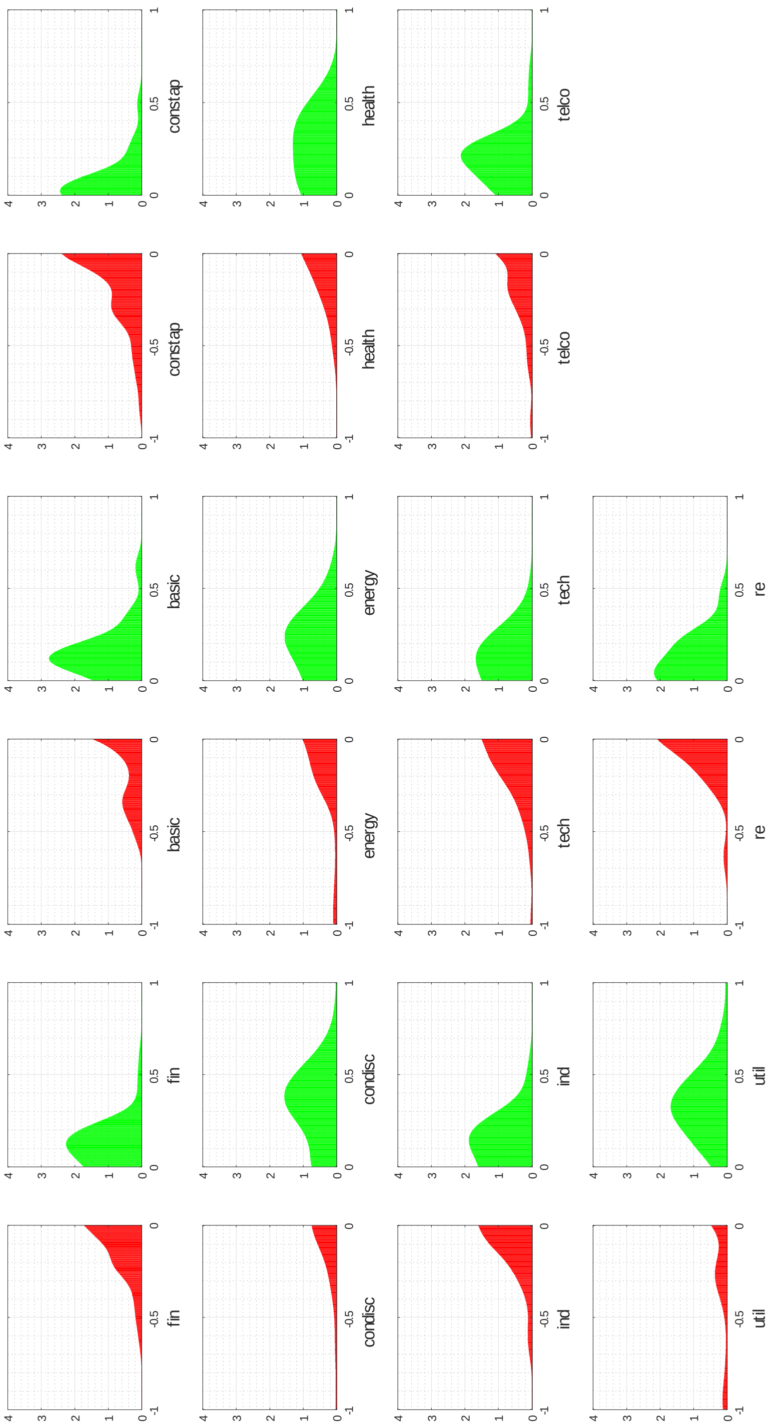

Figure 11: Germany – Estimated Daily Correlations between COVID-19 Cases and Sectoral Stock Price Indexes, Kernels, 2020, 1st half of the year

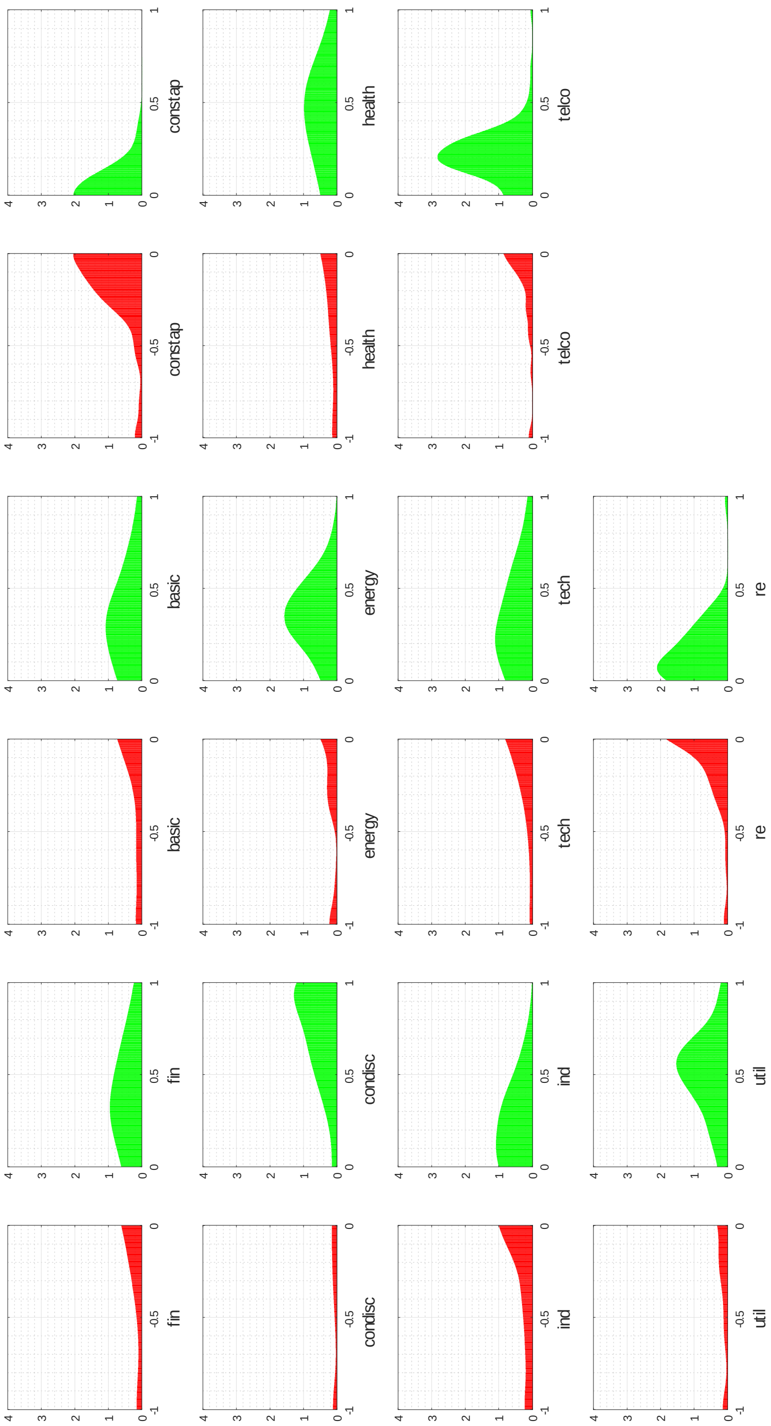

Figure 12: Germany – Estimated Daily Correlations between COVID-19 Cases and Sectoral Stock Price Indexes, Kernels, 2021, 2nd half of the year

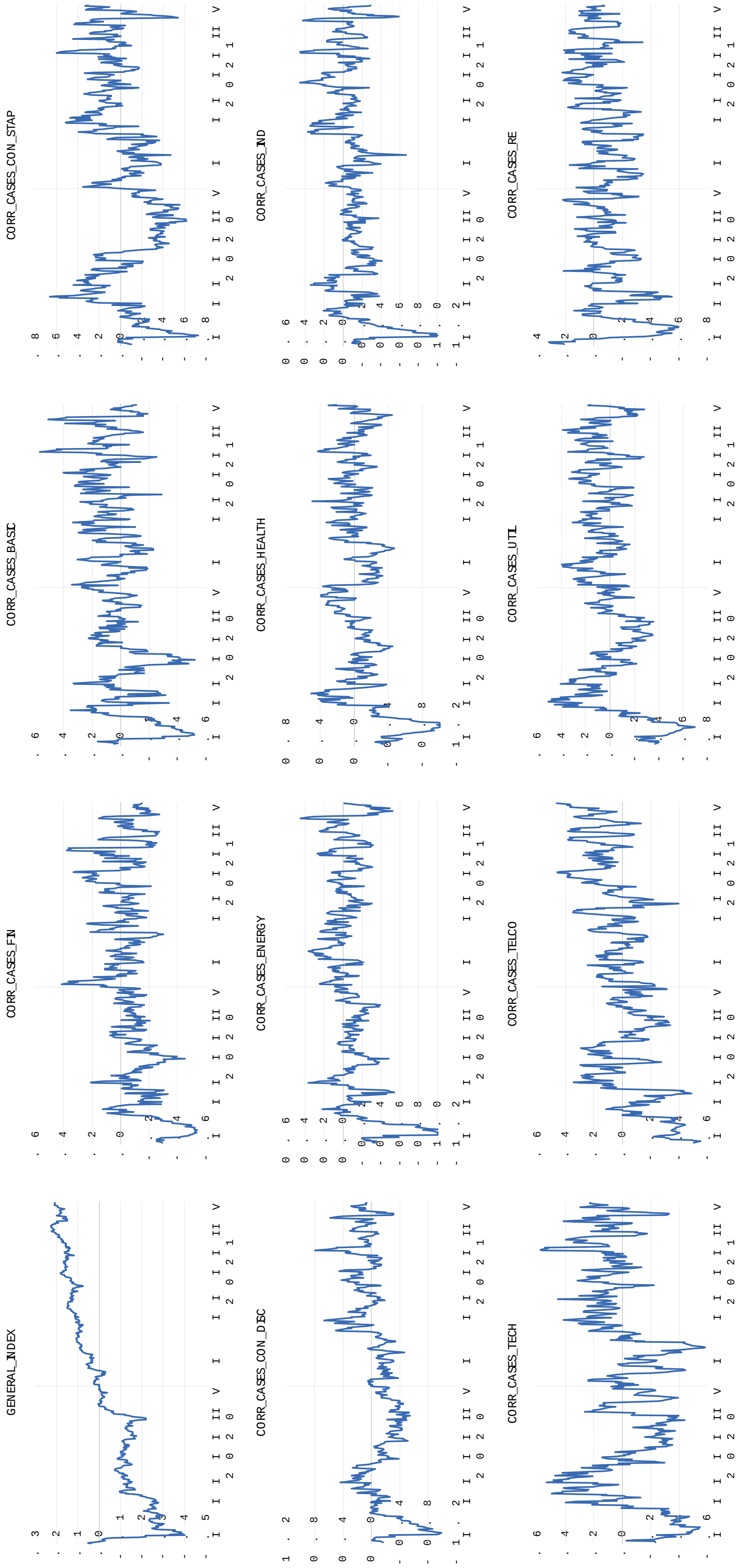

Figure 13: Italy – Estimated Daily Correlations between COVID-19 Cases and Sectoral Stock Price Indexes, Dynamics, 2020-2021

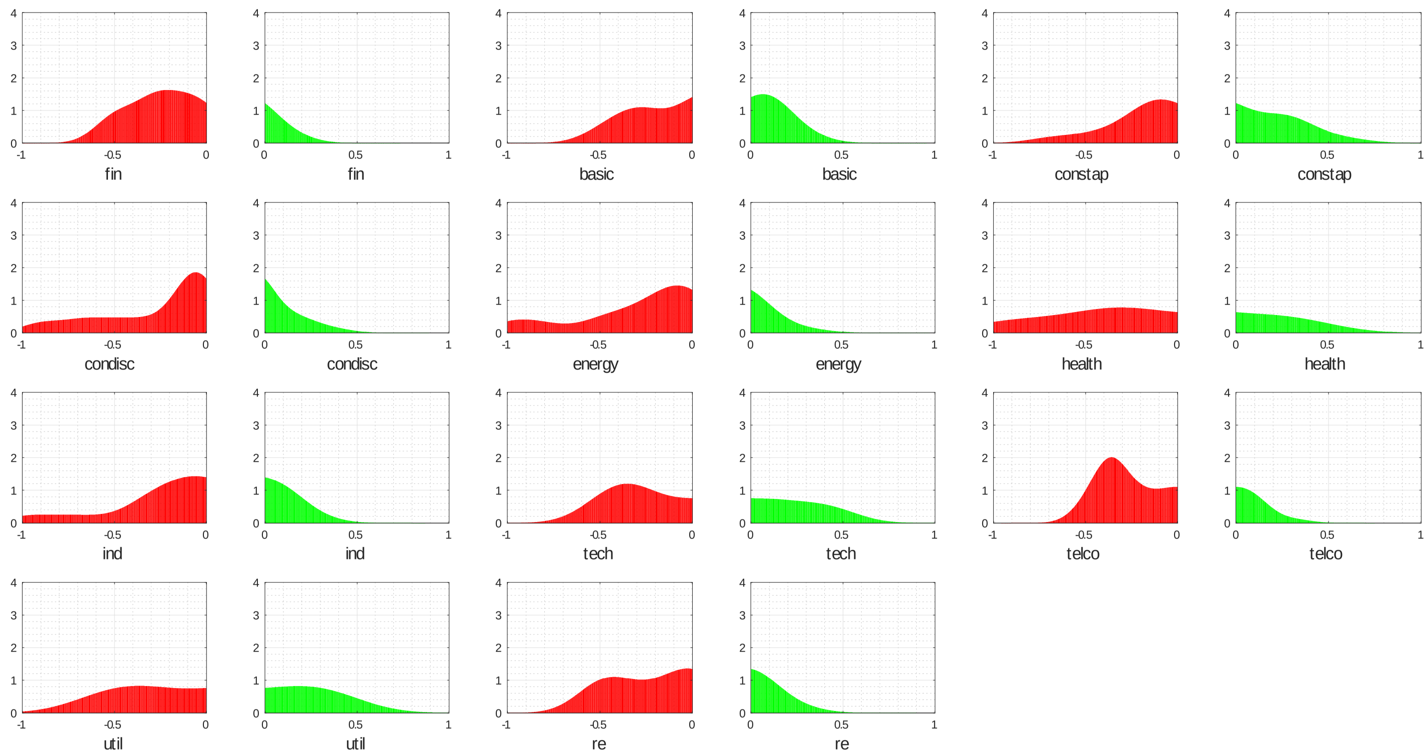

Figure 14: Italy – Estimated Daily Correlations between COVID-19 Cases and Sectoral Stock Price Indexes, Kernels, 2020, 1st half of the year

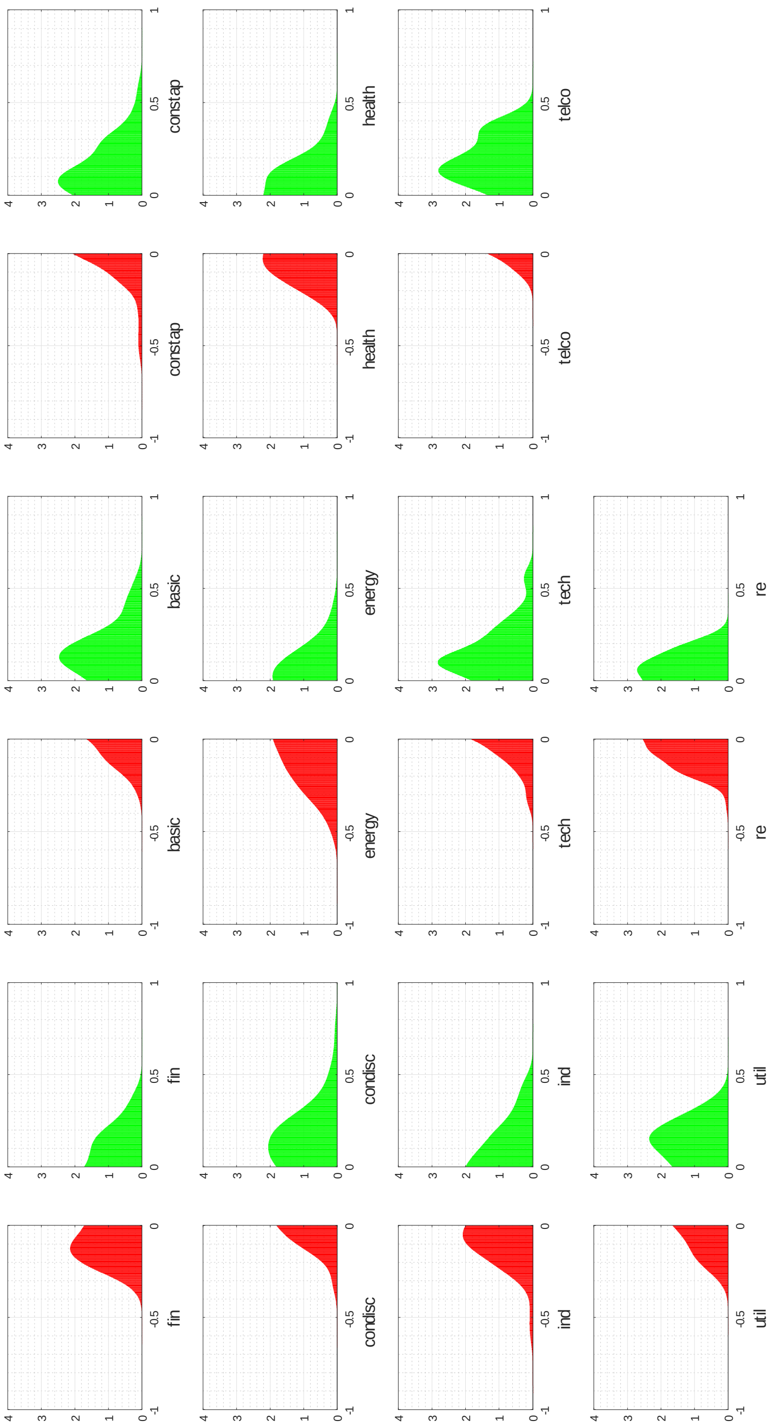

Figure 15: Italy – Estimated Daily Correlations between COVID-19 Cases and Sectoral Stock Price Indexes, Kernels, 2021, 2nd half of the year

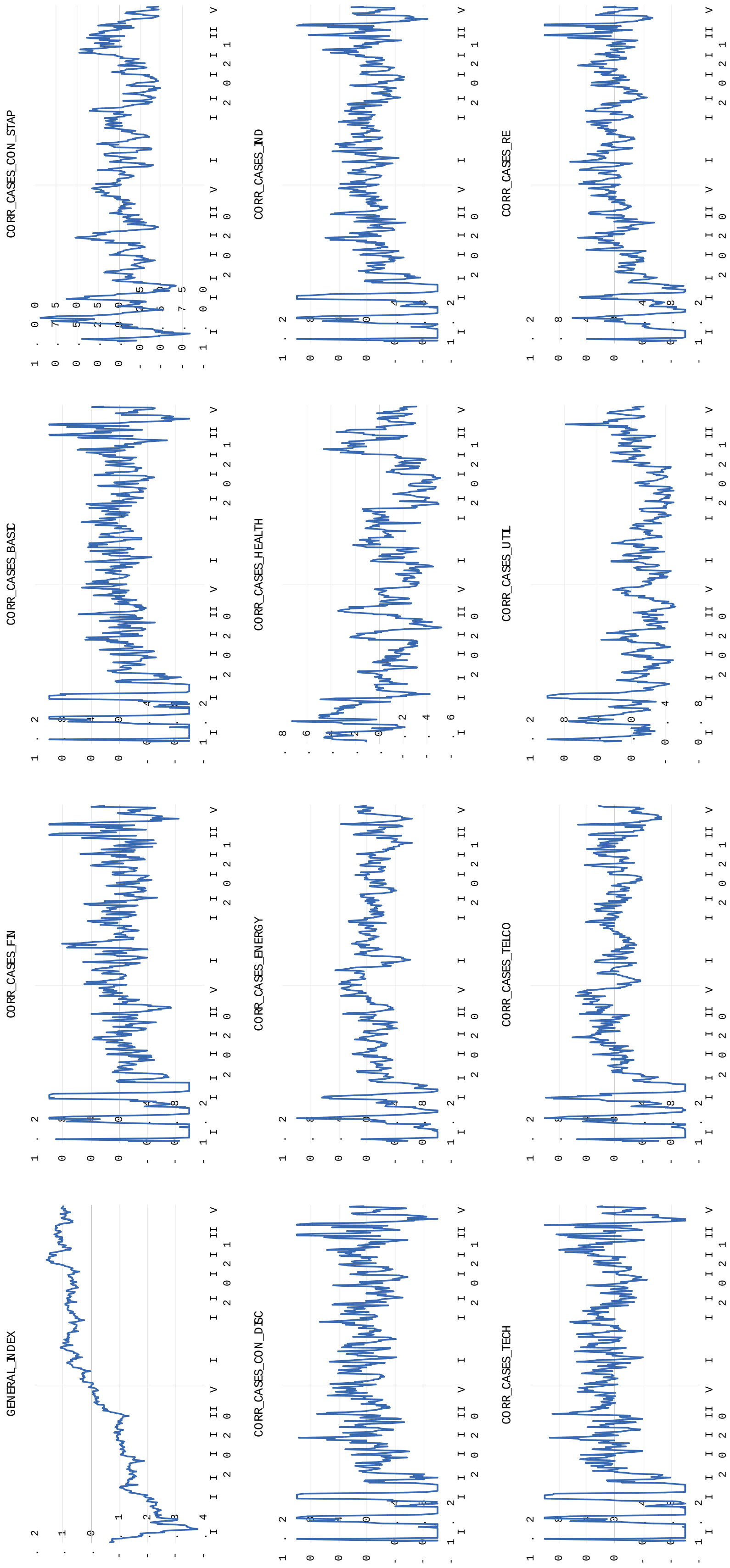

Figure 16: Japan – Estimated Daily Correlations between COVID-19 Cases and Sectoral Stock Price Indexes, Dynamics, 2020-2021

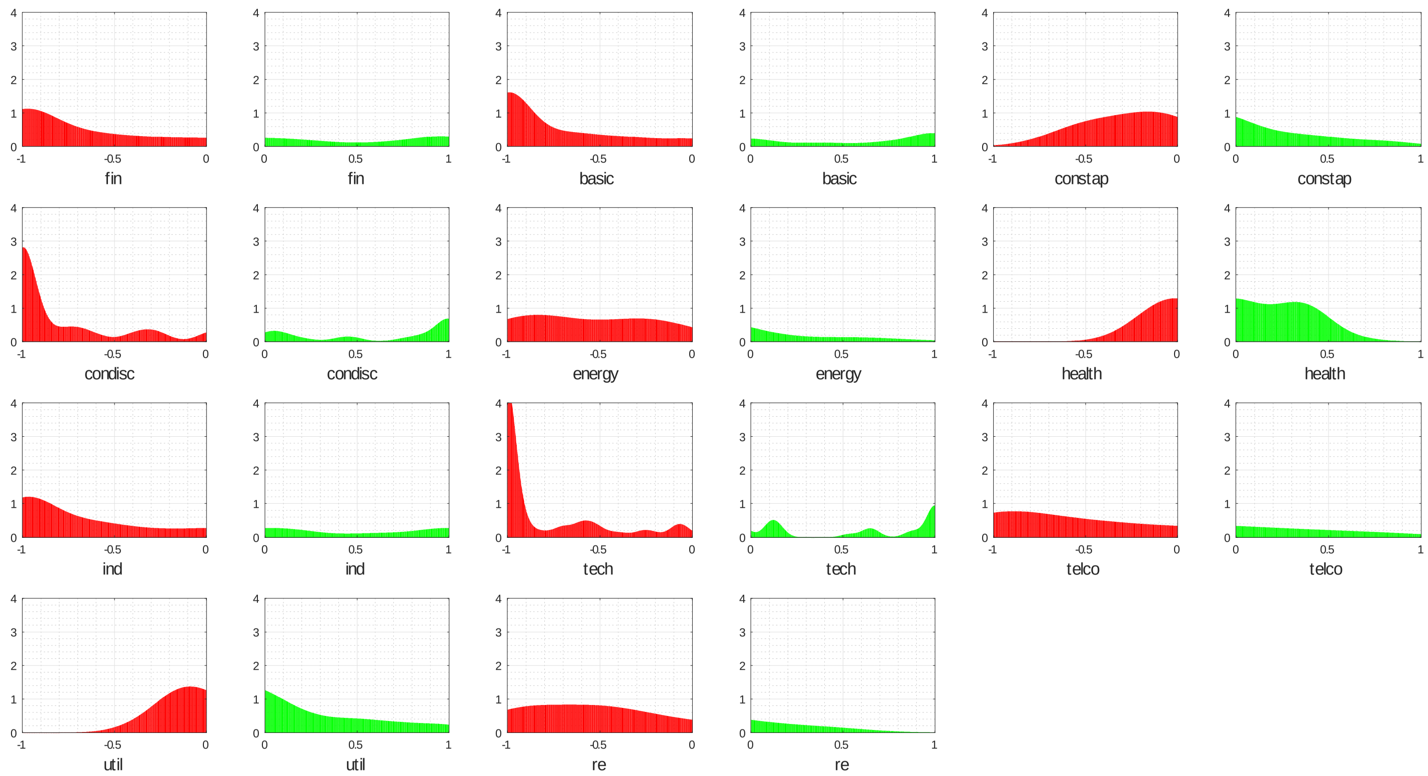

Figure 17: Japan – Estimated Daily Correlations between COVID-19 Cases and Sectoral Stock Price Indexes, Kernels, 2020, 1st half of the year

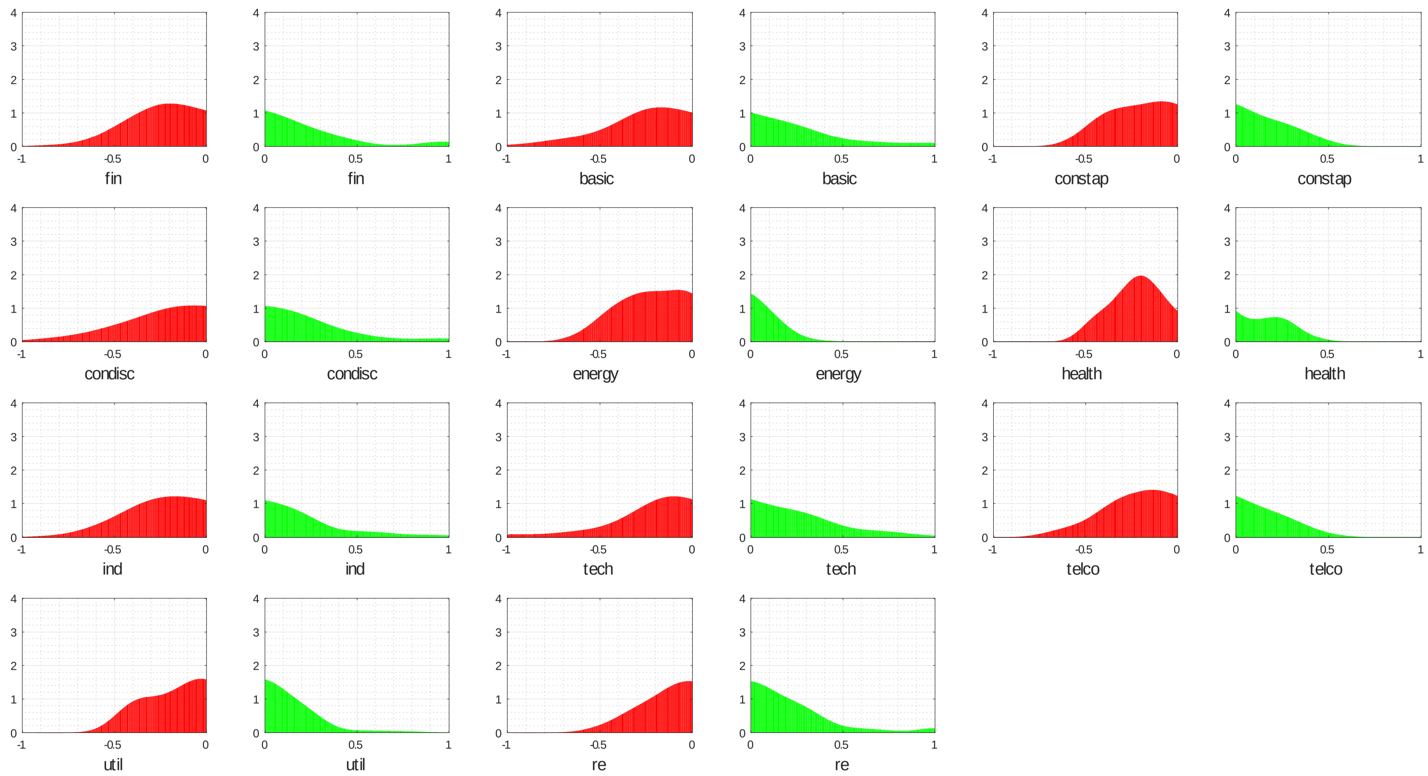

Figure 18: Japan – Estimated Daily Correlations between COVID-19 Cases and Sectoral Stock Price Indexes, Kernels, 2021, 2nd half of the year

	dates (M/D/Y)	value	work days	% change	avg % per work day
PANEL A:	S&P500		COVID-19 Crash		
peak	2/19/20	3386			
trough	3/23/20	2237	23	–33.93%	–1.48%
recovery	8/21/20	3397	109	51.86%	0.48%
PANEL B:	NASDAQ		COVID-19 Crash		
peak	2/19/20	9817			
trough	3/20/20	6880	22	–29.92%	–1.36%
recovery	6/8/20	9925	56	44.26%	0.79%
			GFC Crash		
peak	7/19/07	2720			
trough	3/9/09	1269	427	–53.35%	–0.12%
recovery	1/12/11	2737	482	115.68%	0.24%
			Dotcom Crash		
peak	3/10/00	5049			
trough	10/9/02	1114	673	–77.94%	–0.12%
recovery	4/23/15	5056	3271	353.86%	0.11%

Note: Authors' calculations based on FRED Graph data online. See also Figure 1.

Table 1: The Latest 3 Biggest Stock Market Crashes: A Comparative Perspective

	ω	α	β	$\lvert\alpha+\beta\rvert$	F-LM
Individual Variables					
Basic	1.14E-05**	0.097866*	0.834863*	0.932729	0.016357
Bitcoin	1.73E-04*	0.076191**	0.82542*	0.901611	1.718548
Brent	2.14E-05**	0.33751*	0.681389*	1.018899	0.193392
COVID-19 Cases	0.000425	0.106854*	0.894538*	1.001392	3.644947***
Con. Disc	7.38E-06*	0.074617**	0.86466*	0.939277	3.663041***
Con. Stap	4.07E-06*	0.106068*	0.828277*	0.934345	0.086517
Energy	1.39E-05*	0.07233*	0.885912*	0.958242	0.404173
Financial	8.80E-06*	0.160548*	0.785833*	0.946381	0.906495
Exchange Rate	1.59E-07*	-0.01215	0.99572*	0.983567	0.008099
Gold	3.23E-05*	0.226529*	0.440882*	0.667411	0.480625
Health	5.74E-06**	0.196442*	0.750101*	0.946543	0.320179
Industrial	7.28E-06*	0.196233*	0.754532*	0.950765	0.101647
Real Estate	3.32E-06*	0.058222**	0.904031*	0.962253	0.477513
Technology	1.06E-05**	0.141926*	0.807069*	0.948995	0.831599
Telco	3.94E-06**	0.152062*	0.800567*	0.952629	0.009172
Utility	3.59E-06*	0.021136	0.93081*	0.951946	0.162509
Interest Rate	5.81E-15*	0.298577*	0.64178*	0.940357	0.46289
Summation Terms					
Basic	0.000378	0.104253*	0.89831*	1.002563	3.791185***
Bitcoin	0.000486	0.112996*	0.887713*	1.000709	1.826489
Brent	0.000299	0.094811*	0.908566*	1.003377	2.782121***
Con. Disc	0.000369	0.103948*	0.898737*	1.002685	3.447057***
Con. Stap	0.00037	0.105439*	0.897383*	1.002822	3.90694**
Energy	0.000401	0.102368*	0.899754*	1.002122	3.563154***
Financial	0.000357	0.10163*	0.901421*	1.003051	3.57E-04***
Exchange Rate	0.000427	0.106679*	0.894704*	1.001383	3.443599***
Gold	0.000442	0.108859*	0.892168*	1.001027	3.681151***
Health	0.000314	0.101288*	0.902509*	1.003797	4.478382**
Industrial	0.00035	0.102861*	0.900321*	1.003182	3.689135***
Real Estate	0.000346	0.103321*	0.899985*	1.003306	3.518205***
Technology	0.000321	0.101227*	0.902495*	1.003722	3.588985***
Telco	0.000351	0.103329*	0.899784*	1.003113	4.04121**
Utility	0.000369	0.103609*	0.89907*	1.002679	3.24614***
Interest Rate	0.000425	0.106854*	0.894538*	1.001392	3.644931***

Note:
*, ** and *** denote the rejection of the null hypotheses at 1, 5 and 10%, respectively.
F-LM: ARCH test F-statistics for heteroskedasticity.

Table 2: Univariate GARCH Statistical Significance Test Results, US

	ω	α	β	$\lvert\alpha+\beta\rvert$	F-LM
Individual Variables					
Basic	9.46E-06*	-0.0495*	1.007981*	0.958485	0.105674
Bitcoin	9.86E-05*	0.04416*	0.898548*	0.942708	1.278511
Brent	2.79E-05**	0.228878*	0.749214*	0.978092	0.053784
COVID-19 Cases	2.87E-03**	0.190573*	0.748517*	0.93909	0.466526
Con. Disc	3.29E-06*	0.029557**	0.944619*	0.974176	0.051534
Con. Stap	7.04E-07***	0.037299**	0.945839*	0.983138	0.189931
Energy	0.000383	0.15	0.600000***	0.75	0.011646
Financial	9.34E-07*	-0.01259*	0.997164*	0.984575	0.802944
Exchange Rate	8.30E-08***	-0.00536	0.997696*	0.992337	1.187819
Gold	3.73E-07***	-0.00738	0.999611*	0.992235	0.006284
Health	1.11E-05**	0.127625*	0.793145*	0.92077	0.0000733
Industrial	1.03E-06*	-0.01639*	0.998985*	0.982592	0.460052
Real Estate	1.59E-06***	0.037533**	0.944313*	0.981846	0.222311
Technology	4.34E-06**	0.047987**	0.912586*	0.960573	0.215639
Telco	4.89E-06*	0.020335	0.947932*	0.968267	0.051526
Utility	1.44E-06**	0.027353***	0.951447*	0.9788	1.565442
Interest Rate	3.17E-14*	0.429079*	0.627798*	1.056877	0.522969
Summation Terms					
Basic	2.85E-03**	0.192691*	0.748276*	0.940967	0.404565
Bitcoin	2.53E-03***	0.17432*	0.774753*	0.949073	0.604838
Brent	1.58E-03**	0.112972*	0.849743*	0.962715	0.538951
Con. Disc	3.04E-03**	0.195442*	0.741800*	0.937242	0.224107
Con. Stap	2.99E-03**	0.193527*	0.743509*	0.937036	0.352719
Energy	0.002688**	0.190936*	0.754921*	0.945857	0.220539
Financial	0.003109**	0.197062*	0.738158*	0.93522	0.330454
Exchange Rate	0.002886**	0.188863*	0.750153*	0.939016	0.52772
Gold	0.002855**	0.188913*	0.750600*	0.939513	0.444686
Health	0.003016**	0.189653*	0.746466*	0.936119	0.461801
Industrial	0.003033**	0.194258*	0.742899*	0.937157	0.295776
Real Estate	0.003013**	0.189137*	0.747081*	0.936218	0.32595
Technology	0.003118**	0.183692*	0.749481*	0.933173	0.330127
Telco	0.002831**	0.18891*	0.751965*	0.940875	0.321727
Utility	0.002849**	0.191979*	0.748114*	0.940093	0.306578
Interest Rate	0.002874	0.190573	0.748517	0.93909	0.466511

Note:

*, ** and *** denote the rejection of the null hypotheses at 1, 5 and 10%, respectively.

F-LM: ARCH test F-statistics for heteroskedasticity.

Table 3: Univariate GARCH Statistical Significance Test Results, UK

	ω	α	β	$\lvert\alpha+\beta\rvert$	F-LM
Individual Variables					
Basic	9.68E-07*	-0.018330*	1.004226*	0.985896	0.147078
Bitcoin	5.93E-05**	0.045051*	0.919388*	0.964439	1.70752
Brent	0.0000106	0.286483*	0.758647*	1.04513	0.030558
COVID-19 Cases	0.115	-0.134637	0.607729	0.473092	0.805804
Con. Disc	1.25E-05*	0.178426*	0.763837*	0.942263	0.0000011
Con. Stap	1.40E-05**	0.096777**	0.766442*	0.863219	0.101812
Energy	5.43E-05**	0.095237**	0.778403*	0.87364	1.379554
Financial	5.59E-06**	0.233033*	0.760462*	0.993495	0.700403
Exchange Rate	1.50E-07*	-0.018860**	1.002242*	0.983382	1.519412
Gold	0.0000633	0.15	0.6	0.75	0.591627
Health	2.96E-06*	0.034903***	0.927319*	0.962222	2.101873
Industrial	1.15E-05*	0.215720*	0.727156*	0.942876	0.900102
Real Estate	6.43E-06**	0.148977*	0.774381*	0.923358	1.566438
Technology	9.17E-06**	0.196531*	0.778071*	0.974602	0.119938
Telco	0.000104	0.15	0.600000***	0.75	0.00000384
Utility	3.57E-06*	-0.000832	0.951601*	0.950769	0.142838
Interest Rate	5.64E-13	0.15	0.600000**	0.75	0.15642
Summation Terms					
Basic	0.115	-0.13591	0.612657	0.476747	0.733313
Bitcoin	0.108	-0.1266	0.630976	0.504376	0.035051
Brent	0.117	-0.138291	0.604663	0.466372	0.544994
Con. Disc	0.123	-0.142877	0.590413	0.447536	0.243401
Con. Stap	0.114	-0.13614	0.613237	0.477097	0.657244
Energy	0.126	-0.143286	0.573655	0.430369	0.258312
Financial	0.117	-0.139119	0.605549	0.46643	0.233233
Exchange Rate	0.112	-0.13791	0.626255	0.488345	0.64562
Gold	0.113	-0.135364	0.615426	0.480062	0.762724
Health	0.115	-0.140269	0.617344	0.477075	0.373161
Industrial	0.115	-0.139293	0.614299	0.475006	0.428365
Real Estate	0.114	-0.135273	0.61114	0.475867	0.608137
Technology	0.114	-0.13757	0.617237	0.479667	0.072101
Telco	0.117	-0.13863	0.606666	0.468036	0.291349
Utility	0.12	-0.140344	0.593539	0.453195	0.468217
Interest Rate	0.11	-0.131823	0.625093	0.49327	0.66672

Note:
*, ** and *** denote the rejection of the null hypotheses at 1, 5 and 10%, respectively.
F-LM: ARCH test F-statistics for heteroskedasticity.

Table 4: Univariate GARCH Statistical Significance Test Results, DE

	ω	α	β	$\|\alpha + \beta\|$	F-LM
Individual Variables					
Basic	5.81E-06**	0.090629*	0.888123*	0.978752	0.901
Bitcoin	5.33E-05**	0.063664*	0.905543*	0.969207	0.861
Brent	2.18E-05***	0.423374*	0.639204*	1.062578	0.236
COVID-19 Cases	0.00377	0.100519**	0.855827*	0.956346	0.0309
Con. Disc	1.62E-06*	-0.018196*	1.006357*	0.988161	1.45
Con. Stap	1.17E-06*	-0.020865*	1.006733*	0.985868	0.78
Energy	8.80E-07***	-0.016215*	1.008588*	0.992373	0.282
Financial	7.18E-06**	0.197229*	0.791098*	0.988327	0.53
Exchange Rate	7.32E-08**	-0.012734	1.003702*	0.990968	0.0024
Gold	3.28E-06**	0.001549	0.957976*	0.959525	0.67
Health	2.46E-05*	0.222364*	0.667636*	0.89	0.00239
Industrial	1.19E-06*	-0.020637*	1.008704*	0.988067	0.0829
Real Estate	3.72E-05**	0.167884*	0.691344*	0.859228	0.0495
Technology	1.63E-05**	0.122511*	0.806244*	0.928755	1.23
Telco	1.06E-05***	0.337184*	0.679262*	1.016446	1.44
Utility	1.40E-05*	0.115752*	0.807140*	0.922892	1.21
Interest Rate	1.19E-13*	0.429799*	0.557298*	0.987097	0.0372
Summation Terms					
Basic	0.00394	0.101144**	0.853439*	0.954583	0.0153
Bitcoin	0.00428	0.107520**	0.844721*	0.952241	0.0153
Brent	0.00294	0.085510**	0.880827*	0.966337	0.188
Con. Disc	0.00346	0.103460**	0.856767*	0.960227	0.00589
Con. Stap	0.00347	0.102700**	0.857604*	0.960304	0.0115
Energy	0.00369	0.100868**	0.856457*	0.957325	0.0153
Financial	0.00379	0.101726**	0.854286*	0.956012	0.0198
Exchange Rate	0.00385	0.100069**	0.855373*	0.955442	0.038
Gold	0.00363	0.100265**	0.858052*	0.958317	0.0157
Health	0.00392	0.105194**	0.849463*	0.954657	0.0701
Industrial	0.00369	0.100651**	0.856484*	0.957135	0.00984
Real Estate	0.00386	0.101360**	0.853590*	0.95495	0.0346
Technology	0.00362	0.103639**	0.854839*	0.958478	0.00191
Telco	0.00355	0.099995**	0.859449*	0.959444	0.00379
Utility	0.00371	0.103210**	0.854288*	0.957498	0.000243
Interest Rate	0.00377	0.100518**	0.855827*	0.956345	0.0309

Note:
*, ** and *** denote the rejection of the null hypotheses at 1, 5 and 10%, respectively.
F-LM: ARCH test F-statistics for heteroskedasticity.

Table 5: Univariate GARCH Statistical Significance Test Results, IT

	ω	α	β	$\lvert\alpha+\beta\rvert$	F-LM
Individual Variables					
Basic	4.52E-05*	0.319641*	0.430403*	0.750044	0.00449
Bitcoin	1.66E-04**	0.167190*	0.770982*	0.938172	0.482
Brent	3.29E-05**	0.418130*	0.638093*	1.056223	0.0395
COVID-19 Cases	4.43E-03**	0.130867*	0.812723*	0.94359	0.0919
Con. Disc	2.66E-05*	0.295958*	0.506431*	0.802389	0.0775
Con. Stap	1.46E-05**	0.216141*	0.599849*	0.81599	0.0744
Energy	3.15E-05**	0.132005**	0.701844*	0.833849	0.103
Financial	1.43E-06*	-0.012513	0.998286*	0.985773	7.96E+00*
Exchange Rate	1.86E-06**	0.198018*	0.671096*	0.869114	1.19
Gold	0.000000174	-0.006391	1.001756*	0.995365	0.0109
Health	2.82E-05**	0.243703*	0.538909*	0.782612	0.23
Industrial	2.45E-05*	0.237795*	0.594337*	0.832132	0.413
Real Estate	6.76E-06**	0.198007*	0.754734*	0.952741	0.0228
Technology	3.59E-05*	0.209092*	0.543883*	0.752975	0.0755
Telco	1.97E-05*	0.206585*	0.662516*	0.869101	0.000648
Utility	0.0000137	0.173275	0.713159	0.886434	0.000938
Interest Rate	4.61E-15	0.435764	0.700149	1.135913	1.31
Summation Terms					
Basic	5.24E-03**	0.148041*	0.786430*	0.934471	0.0991
Bitcoin	1.30E-02**	0.223803*	0.630966*	0.854769	0.000249
Brent	3.29E-03**	0.104789*	0.850122*	0.954911	0.158
Con. Disc	5.18E-03**	0.147846*	0.787466*	0.935312	0.096
Con. Stap	4.49E-03**	0.133496*	0.809208*	0.942704	0.102
Energy	4.77E-03**	0.136369*	0.802795*	0.939164	0.217
Financial	5.10E-03**	0.146023*	0.790114*	0.936137	0.102
Exchange Rate	4.41E-03**	0.130692*	0.813040*	0.943732	0.0901
Gold	4.48E-03**	0.134448*	0.808964*	0.943412	0.106
Health	4.30E-03**	0.131082*	0.813793*	0.944875	0.139
Industrial	4.99E-03**	0.144054*	0.793175*	0.937229	0.118
Real Estate	4.84E-03**	0.139198*	0.799807*	0.939005	0.129
Technology	5.23E-03**	0.146147*	0.788883*	0.93503	0.0985
Telco	4.80E-03**	0.138056*	0.801417*	0.939473	0.11
Utility	4.36E-03**	0.134225*	0.810054*	0.944279	0.112
Interest Rate	4.43E-03**	0.130867*	0.812723*	0.94359	0.0919

Note:

*, ** and *** denote the rejection of the null hypotheses at 1, 5 and 10%, respectively.

F-LM: ARCH test F-statistics for heteroskedasticity.

Table 6: Univariate GARCH Statistical Significance Test Results, JP

lag	usfin	usbas	usstap	usdisc	usengy	ushlth	usind	ustech	ustel	usutil	usre
1	0.6956	0.7574	0.4184	0.6744	0.3472	0.2314	0.8951	0.6345	0.9643	0.6952	0.8917
2	0.4779	0.8396	0.5872	0.8919	0.4074	0.4757	0.9846	0.9272	0.9139	0.7215	0.5938
3	0.0323	0.1563	0.0772	0.1420	0.3664	0.0518	0.0690	0.1398	0.0371	0.0801	0.0718
4	0.0078	0.0361	0.0060	0.0646	0.2432	0.0248	0.0101	0.1166	0.0047	0.0099	0.0173
5	0.0023	0.0092	0.0037	0.0480	0.0018	0.0580	0.0060	0.0624	0.0061	0.0096	0.0005
6	0.0017	0.0094	0.0086	0.0486	0.0020	0.0755	0.0018	0.1090	0.0102	0.0076	0.0004
7	0.0325	0.0432	0.1340	0.1065	0.0563	0.2666	0.0195	0.3736	0.1177	0.0244	0.0069
8	0.0011	0.0062	0.0033	0.0062	0.0142	0.1473	0.0002	0.1013	0.0075	0.0012	0.0000
9	0.0001	0.0013	0.0052	0.0035	0.0113	0.0903	0.0000	0.0520	0.0002	0.0005	0.0000
10	0.0019	0.0015	0.0163	0.0039	0.0092	0.0029	0.0000	0.0878	0.0007	0.0100	0.0000
11	0.0077	0.0060	0.1112	0.0142	0.0088	0.0147	0.0001	0.2562	0.0116	0.0034	0.0000
12	0.0905	0.0821	0.2780	0.1578	0.0609	0.0296	0.0165	0.5986	0.0292	0.0135	0.0449
13	0.1290	0.1027	0.5774	0.3243	0.0697	0.1119	0.0183	0.8020	0.1175	0.0582	0.0501
14	0.0203	0.0147	0.3334	0.0194	0.0179	0.0158	0.0010	0.3327	0.0581	0.0102	0.0047
15	0.0205	0.0056	0.1678	0.0094	0.0203	0.0016	0.0004	0.2463	0.0525	0.0083	0.0094
lag	ukfin	ukbas	ukstap	ukdisc	ukengy	ukhlth	ukind	uktech	uktel	ukutil	ukre
1	0.7663	0.9687	0.8517	0.8309	0.1101	0.7727	0.8340	0.9143	0.3364	0.1791	0.2980
2	0.4362	0.7663	0.5566	0.3528	0.0123	0.6088	0.1607	0.1051	0.1629	0.3681	0.6748
3	0.0913	0.3787	0.8691	0.1580	0.0335	0.8352	0.0218	0.0246	0.3002	0.1929	0.0618
4	0.4372	0.4296	0.4473	0.5645	0.0321	0.6111	0.2997	0.6191	0.2509	0.3995	0.1087
5	0.0103	0.0033	0.0000	0.1198	0.0001	0.0555	0.0158	0.5611	0.0000	0.0156	0.0103
6	0.0001	0.0061	0.0000	0.0106	0.0003	0.0506	0.0028	0.5142	0.0000	0.0074	0.0039
7	0.1045	0.0344	0.0010	0.6691	0.0004	0.1253	0.2996	0.9571	0.0003	0.5603	0.5154
8	0.1669	0.0996	0.0028	0.7482	0.0029	0.1804	0.4544	0.9874	0.0008	0.0215	0.6818
9	0.1213	0.0447	0.0033	0.8863	0.0007	0.2216	0.3945	0.8072	0.0032	0.0170	0.3684
10	0.0247	0.0078	0.0212	0.2011	0.0002	0.6571	0.0633	0.8851	0.0065	0.0527	0.1914
11	0.0206	0.0090	0.0375	0.3692	0.0021	0.1814	0.1894	0.8372	0.0097	0.0138	0.2349
12	0.0260	0.0283	0.1149	0.3562	0.0058	0.3848	0.2141	0.9039	0.0108	0.0197	0.4569
13	0.0243	0.0238	0.2626	0.1657	0.0005	0.2446	0.2381	0.8719	0.0393	0.0578	0.2996
14	0.0037	0.0074	0.0442	0.0374	0.0000	0.1041	0.0935	0.2765	0.0048	0.0440	0.1407
15	0.0568	0.2090	0.1121	0.2445	0.0159	0.2471	0.6076	0.2991	0.0191	0.0255	0.4390

Table 7: Granger Causality Test Results, US and UK, p-values

lag	cafin	cabas	castap	cadisc	caengy	cahlth	caind	catech	catel	cautil	care
1	0.4389	0.9020	0.0133	0.2014	0.4807	0.6662	0.4711	0.2673	0.2426	0.3488	0.5023
2	0.0000	0.6406	0.0001	0.0000	0.0000	0.1750	0.0000	0.0065	0.0001	0.0004	0.0010
3	0.0000	0.3615	0.0000	0.0000	0.0000	0.0292	0.0000	0.0088	0.0000	0.0000	0.0000
4	0.0000	0.5948	0.0009	0.0000	0.0000	0.3901	0.0000	0.0266	0.0001	0.0000	0.0000
5	0.0000	0.0257	0.0362	0.0000	0.0026	0.4608	0.0016	0.0211	0.0020	0.0001	0.0000
6	0.0013	0.0289	0.2395	0.0009	0.1665	0.9761	0.2038	0.5197	0.1458	0.0018	0.0000
7	0.0251	0.0336	0.4181	0.0006	0.2263	0.8753	0.0347	0.1773	0.2547	0.0276	0.0001
8	0.0001	0.0020	0.0496	0.0005	0.0660	0.7247	0.0145	0.1700	0.0271	0.0001	0.0074
9	0.0000	0.0027	0.0018	0.0000	0.0248	0.6836	0.0006	0.2236	0.0000	0.0000	0.0002
10	0.0000	0.0000	0.0108	0.0000	0.0265	0.7727	0.0025	0.2413	0.0001	0.0000	0.0000
11	0.0000	0.0004	0.0013	0.0000	0.0280	0.8131	0.0010	0.3249	0.0000	0.0000	0.0069
12	0.0017	0.1679	0.1178	0.0028	0.1238	0.9448	0.1138	0.7196	0.0005	0.0000	0.1592
13	0.1650	0.1966	0.3735	0.3945	0.5483	0.9987	0.4584	0.6807	0.2551	0.0668	0.9707
14	0.2560	0.2293	0.2740	0.3310	0.5517	0.9902	0.6242	0.7558	0.1321	0.0852	0.7268
15	0.0585	0.0859	0.1947	0.1628	0.7103	0.9852	0.7213	0.7438	0.2186	0.0635	0.7000
lag	aufin	aubas	austap	audisc	auengy	auhlth	auind	autech	autel	auutil	aure
1	0.0174	0.4054	0.0008	0.1351	0.3319	0.0067	0.1810	0.1353	0.0505	0.0625	0.0468
2	0.0474	0.5781	0.0025	0.2103	0.3328	0.0014	0.2973	0.2216	0.0430	0.1333	0.0840
3	0.0147	0.0008	0.0017	0.0454	0.0084	0.0031	0.0084	0.0261	0.0056	0.0132	0.1054
4	0.0115	0.0015	0.0007	0.0545	0.0166	0.0103	0.0121	0.0408	0.0091	0.0304	0.1872
5	0.0516	0.0043	0.0060	0.1959	0.0886	0.0455	0.0670	0.1373	0.0509	0.0985	0.2136
6	0.0641	0.0071	0.0228	0.1823	0.1385	0.0423	0.0272	0.0035	0.0815	0.1274	0.1485
7	0.1192	0.0065	0.0606	0.0980	0.2013	0.0783	0.0043	0.0001	0.1341	0.2057	0.0493
8	0.1646	0.0172	0.1272	0.1312	0.1635	0.1525	0.0086	0.0004	0.2876	0.3203	0.0352
9	0.1116	0.0307	0.1460	0.0593	0.1642	0.0236	0.0018	0.0002	0.2199	0.1769	0.0186
10	0.2296	0.0413	0.1985	0.1469	0.1971	0.0413	0.0051	0.0004	0.2162	0.1409	0.1060
11	0.1432	0.0344	0.1669	0.2812	0.2716	0.0590	0.0111	0.0018	0.1821	0.1735	0.1136
12	0.0005	0.0556	0.1124	0.2079	0.2369	0.0209	0.0021	0.0023	0.1529	0.0750	0.0112
13	0.0000	0.1143	0.0854	0.0588	0.3296	0.0335	0.0009	0.0091	0.2262	0.2308	0.0026
14	0.0001	0.1180	0.1438	0.0907	0.3917	0.0610	0.0012	0.0164	0.3453	0.2949	0.0051
15	0.0000	0.1143	0.1839	0.0201	0.0562	0.1174	0.0008	0.0377	0.3451	0.0675	0.0014

Table 8: Granger Causality Test Results, Canada and Australia, p-values

lag	defin	debas	destap	dedisc	deengy	dehlth	deind	detech	detel	deutil	dere
1	0.0584	0.0079	0.1740	0.0228	0.1097	0.2809	0.0734	0.3765	0.2179	0.9405	0.1149
2	0.0476	0.0068	0.1966	0.0555	0.0632	0.3268	0.1110	0.3859	0.1283	0.9712	0.1031
3	0.0732	0.0174	0.3426	0.1003	0.0794	0.5518	0.2193	0.5747	0.2808	0.8929	0.1943
4	0.0235	0.0032	0.5030	0.0028	0.0738	0.3694	0.0103	0.3383	0.0367	0.7843	0.0192
5	0.0243	0.0162	0.0410	0.0101	0.1332	0.2492	0.0335	0.3628	0.0146	0.2914	0.0023
6	0.0050	0.0008	0.2177	0.0017	0.1830	0.1068	0.0043	0.0720	0.0030	0.2174	0.0103
7	0.0033	0.0149	0.2297	0.0156	0.5005	0.5263	0.0045	0.0746	0.1479	0.5522	0.0530
8	0.0008	0.0046	0.1186	0.0124	0.5925	0.0130	0.0039	0.1137	0.0429	0.0565	0.0288
9	0.0022	0.0140	0.6034	0.0402	0.7485	0.0334	0.0084	0.1851	0.0380	0.1096	0.0193
10	0.1820	0.1157	0.3644	0.4028	0.3958	0.1622	0.1114	0.5892	0.4684	0.3017	0.1442
11	0.3153	0.1567	0.4463	0.4682	0.4942	0.2191	0.1485	0.7277	0.5409	0.2578	0.2184
12	0.7207	0.7044	0.4972	0.8484	0.5421	0.1451	0.4751	0.8840	0.5124	0.2370	0.5078
13	0.6802	0.6061	0.2558	0.6545	0.6153	0.0931	0.2947	0.8575	0.0840	0.0962	0.0255
14	0.0763	0.0319	0.2277	0.4239	0.2866	0.0548	0.1001	0.9134	0.0316	0.0926	0.0610
15	0.2423	0.1205	0.3143	0.3667	0.1858	0.2485	0.2040	0.8527	0.0691	0.0889	0.0584
lag	frfin	frbas	frstap	frdisc	frengy	frhlth	frind	frtech	frtel	frutil	frre
1	0.3486	0.0883	0.6101	0.5995	0.2889	0.0907	0.2578	0.9781	0.2531	0.0454	0.4407
2	0.1862	0.0257	0.7928	0.5556	0.2867	0.1193	0.0952	0.1239	0.3454	0.0776	0.7400
3	0.1861	0.0161	0.8786	0.3855	0.4041	0.0939	0.0708	0.0388	0.3088	0.1185	0.7732
4	0.1379	0.0270	0.4320	0.3651	0.4875	0.0575	0.0757	0.0180	0.2108	0.0884	0.2603
5	0.0474	0.0440	0.0613	0.1521	0.3351	0.0157	0.0168	0.0224	0.1333	0.0006	0.0314
6	0.0022	0.0234	0.0155	0.0254	0.0219	0.0638	0.0010	0.0134	0.1513	0.0003	0.0128
7	0.0545	0.0950	0.1893	0.2844	0.6106	0.2408	0.0122	0.0518	0.6001	0.0144	0.0708
8	0.0371	0.2617	0.1981	0.3698	0.3844	0.5125	0.0073	0.0502	0.6150	0.0318	0.0406
9	0.0177	0.2246	0.1626	0.4681	0.4628	0.5848	0.0131	0.0702	0.6963	0.0429	0.0425
10	0.2997	0.1830	0.6057	0.7652	0.6406	0.6140	0.0601	0.1531	0.4108	0.3948	0.4116
11	0.3060	0.2692	0.7036	0.7596	0.6172	0.6306	0.0633	0.2101	0.4009	0.3243	0.6654
12	0.3882	0.0747	0.7611	0.7565	0.6407	0.5305	0.1920	0.1510	0.0363	0.5962	0.6381
13	0.3561	0.0706	0.6794	0.7319	0.6146	0.5490	0.2775	0.1371	0.3541	0.4171	0.8421
14	0.4208	0.0535	0.7620	0.4327	0.2503	0.5104	0.1687	0.1529	0.4460	0.6415	0.8306
15	0.4022	0.1146	0.8162	0.2986	0.2976	0.5470	0.1002	0.0957	0.5865	0.6838	0.5198

Table 9: Granger Causality Test Results, Germany and France, p-values

lag	itfin	itbas	itstap	itdisc	itengy	ithlth	itind	ittech	ittel	itutil	itre
1	0.6946	0.6565	0.6525	0.7579	0.3762	0.0330	0.9089	0.7449	0.3737	0.7208	0.2454
2	0.9843	0.1673	0.3191	0.9050	0.5996	0.0691	0.7911	0.8646	0.7759	0.5386	0.5480
3	0.9933	0.3905	0.3412	0.9412	0.1844	0.1407	0.9686	0.7895	0.5674	0.7897	0.5965
4	0.9948	0.4609	0.4219	0.9368	0.2667	0.0916	0.9672	0.7537	0.7789	0.9105	0.7540
5	0.5868	0.3001	0.0291	0.3006	0.0843	0.0772	0.1749	0.2058	0.5042	0.3478	0.0673
6	0.0013	0.0118	0.0037	0.0133	0.0002	0.0008	0.0008	0.0433	0.0051	0.0000	0.0103
7	0.0017	0.0059	0.0011	0.0115	0.0000	0.0011	0.0010	0.0203	0.0028	0.0000	0.0128
8	0.0044	0.0269	0.0048	0.3567	0.0353	0.0011	0.0036	0.0435	0.0081	0.0003	0.0227
9	0.0867	0.4711	0.0588	0.1901	0.1124	0.0118	0.1099	0.1090	0.1073	0.0142	0.0969
10	0.1095	0.5364	0.0532	0.1369	0.1173	0.0090	0.0868	0.1160	0.0434	0.0099	0.0632
11	0.1047	0.6456	0.0422	0.1383	0.1556	0.0107	0.0328	0.1230	0.0575	0.0166	0.0161
12	0.7693	0.4248	0.0806	0.5484	0.0103	0.1901	0.4258	0.7117	0.0240	0.7033	0.0921
13	0.5119	0.5829	0.0764	0.6518	0.0101	0.4430	0.4368	0.7387	0.0338	0.8690	0.1159
14	0.7970	0.6437	0.1898	0.6805	0.0150	0.5904	0.5731	0.6287	0.0553	0.9161	0.2853
15	0.6435	0.6663	0.1573	0.6268	0.0548	0.6025	0.6328	0.4830	0.1430	0.9549	0.3319
lag	esfin	esbas	esstap	esdisc	esengy	eshlth	esind	estech	estel	esutil	esre
1	0.1558	0.0696	0.9283	0.0807	0.0382	0.8934	0.1725	0.1498	0.1466	0.6181	0.1368
2	0.3775	0.1938	0.4104	0.1683	0.1125	0.9338	0.4311	0.2976	0.4113	0.9324	0.3338
3	0.4331	0.2962	0.5663	0.3080	0.1914	0.9732	0.5495	0.4508	0.4444	0.6858	0.2889
4	0.2290	0.0395	0.7138	0.1867	0.1970	0.6826	0.2267	0.4273	0.0253	0.4277	0.3171
5	0.0059	0.0018	0.5524	0.0019	0.0024	0.0849	0.0002	0.0003	0.0007	0.0246	0.0009
6	0.0001	0.0001	0.3906	0.0001	0.0002	0.0606	0.0000	0.0007	0.0002	0.0014	0.0000
7	0.0019	0.0009	0.4682	0.0002	0.0011	0.1949	0.0000	0.0031	0.0003	0.0055	0.0001
8	0.0007	0.0009	0.6632	0.0002	0.0044	0.2679	0.0000	0.0089	0.0006	0.0798	0.0003
9	0.0848	0.0724	0.2362	0.0067	0.1193	0.0888	0.0046	0.0239	0.0094	0.0905	0.0020
10	0.1353	0.1292	0.0047	0.0330	0.0505	0.0360	0.0119	0.0202	0.0258	0.1624	0.0065
11	0.0687	0.0671	0.0001	0.0524	0.0285	0.0246	0.0275	0.0304	0.0199	0.0454	0.0071
12	0.3725	0.2661	0.0003	0.0732	0.3556	0.1116	0.0573	0.0799	0.0458	0.7190	0.1174
13	0.3411	0.3094	0.0029	0.0827	0.1510	0.1605	0.0240	0.0693	0.0524	0.8170	0.1001
14	0.2189	0.3687	0.0016	0.1322	0.0957	0.0453	0.1143	0.2829	0.0080	0.3597	0.3345
15	0.2222	0.2893	0.0745	0.1652	0.0059	0.1900	0.0319	0.2524	0.0614	0.6176	0.2544

Table 10: Granger Causality Test Results, Italy and Spain, p-values

lag	cnfin	cnbas	cnstap	cndisc	cnengy	cnhlth	cnind	cntech	cntel	cnutil	cnre
1	0.7408	0.9188	0.6151	0.4402	0.5316	0.8982	0.5741	0.4972	0.8223	0.9866	0.9434
2	0.7631	0.8877	0.9222	0.5050	0.2827	0.5549	0.5528	0.3193	0.2050	0.8557	0.9623
3	0.7356	0.8939	0.9814	0.6408	0.1758	0.6478	0.6976	0.3425	0.2254	0.8909	0.9935
4	0.8761	0.8958	0.9848	0.7614	0.1878	0.7527	0.8496	0.4936	0.3565	0.7005	0.9906
5	0.7005	0.6620	0.9577	0.2246	0.1697	0.8506	0.2767	0.3746	0.1803	0.4833	0.7988
6	0.6668	0.5538	0.5886	0.0981	0.2107	0.7439	0.2307	0.0972	0.0656	0.3348	0.6959
7	0.5280	0.2200	0.4527	0.0229	0.2347	0.3679	0.0809	0.0491	0.0163	0.3450	0.5782
8	0.6281	0.1928	0.6315	0.0397	0.2159	0.3278	0.0844	0.0822	0.0271	0.4347	0.5955
9	0.5523	0.1877	0.4197	0.0188	0.4100	0.2815	0.0573	0.0292	0.0086	0.3419	0.6563
10	0.7158	0.3023	0.5994	0.0606	0.4387	0.3472	0.0988	0.0619	0.0292	0.3487	0.7578
11	0.7012	0.4091	0.7316	0.0903	0.4771	0.5227	0.1539	0.0566	0.0186	0.4693	0.8337
12	0.7599	0.4570	0.7622	0.1294	0.5479	0.5624	0.0888	0.0648	0.0140	0.5789	0.6625
13	0.7678	0.5129	0.7762	0.1662	0.5897	0.6214	0.1229	0.0875	0.0227	0.6340	0.6980
14	0.8111	0.5726	0.8363	0.2394	0.5437	0.7091	0.1808	0.1319	0.0330	0.6660	0.4003
15	0.0130	0.2182	0.6129	0.0304	0.0589	0.6969	0.0247	0.0116	0.0027	0.6797	0.1932
lag	jpfin	jpbas	jpstap	jpdisc	jpengy	jphlth	jpin	jptech	jptel	jputil	jpre
1	0.9087	0.9871	0.9210	0.3822	0.5215	0.6873	0.9126	0.7579	0.8219	0.8439	0.8373
2	0.7065	0.9543	0.6353	0.4727	0.1787	0.6181	0.7624	0.6101	0.4397	0.7286	0.3466
3	0.8497	0.9802	0.7907	0.6609	0.3169	0.7647	0.8505	0.8102	0.6677	0.9171	0.5053
4	0.8169	0.9156	0.8700	0.7920	0.4217	0.8932	0.8993	0.7682	0.6421	0.9393	0.5496
5	0.4301	0.4089	0.8517	0.6162	0.2207	0.9405	0.4631	0.6098	0.5103	0.7257	0.1655
6	0.4107	0.3952	0.8713	0.3636	0.4356	0.9690	0.3572	0.8063	0.7984	0.8942	0.0217
7	0.5173	0.5629	0.9044	0.5063	0.3140	0.9900	0.4869	0.8378	0.6498	0.8567	0.0492
8	0.2913	0.2116	0.7998	0.2367	0.9880	0.3079	0.2371	0.5668	0.5276	0.6449	0.0222
9	0.4782	0.3099	0.9302	0.2050	0.5225	0.9037	0.3412	0.6302	0.7367	0.9228	0.0179
10	0.2711	0.1484	0.5972	0.0175	0.1988	0.7390	0.0884	0.1558	0.2702	0.8441	0.0003
11	0.2074	0.1912	0.3731	0.0150	0.1166	0.4907	0.0605	0.0249	0.2511	0.7535	0.0003
12	0.0004	0.0194	0.2147	0.0017	0.0578	0.1202	0.0045	0.0028	0.0685	0.4553	0.0000
13	0.0002	0.0027	0.0878	0.0004	0.0360	0.1085	0.0010	0.0011	0.1232	0.1801	0.0000
14	0.0003	0.0062	0.0796	0.0007	0.0666	0.1721	0.0014	0.0008	0.2380	0.1912	0.0000
15	0.0031	0.0057	0.1388	0.0024	0.1039	0.5501	0.0048	0.0063	0.3610	0.1896	0.0001

Table 11: Granger Causality Test Results, China and Japan, p-values

lag	infin	inbas	instap	indisc	inengy	inhlth	inind	intech	intel	inutil	inre
1	0.1622	0.7458	0.9149	0.2135	0.6865	0.5842	0.0795	0.5149	0.8193	0.5186	0.7360
2	0.0126	0.4265	0.4719	0.0911	0.2470	0.2820	0.0131	0.3638	0.6849	0.1087	0.3017
3	0.0124	0.0426	0.6820	0.0164	0.1584	0.3589	0.0009	0.2321	0.2252	0.3280	0.1708
4	0.0079	0.0190	0.5586	0.0129	0.3141	0.3534	0.0006	0.3488	0.2560	0.4151	0.2460
5	0.0120	0.0026	0.0018	0.0275	0.0548	0.0000	0.0020	0.0765	0.2156	0.2440	0.2197
6	0.0012	0.0375	0.2294	0.0021	0.0572	0.0061	0.0022	0.1639	0.0768	0.4786	0.2163
7	0.0000	0.0000	0.0000	0.0000	0.0014	0.0002	0.0000	0.0006	0.1259	0.0207	0.0281
8	0.0000	0.0003	0.0000	0.0000	0.0024	0.0000	0.0000	0.1022	0.0708	0.0553	0.1851
9	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0003	0.0000	0.0043	0.0005
10	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0018	0.0046	0.2360	0.0003
11	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0028	0.0821	0.0008
12	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0004	0.0100	0.0002
13	0.0023	0.1177	0.0000	0.0112	0.0000	0.0013	0.4482	0.1097	0.0208	0.6324	0.0105
14	0.0002	0.0559	0.0000	0.0003	0.0000	0.0024	0.0827	0.0019	0.0322	0.5073	0.0103
15	0.0191	0.3850	0.0000	0.0191	0.0014	0.0020	0.5946	0.0044	0.1147	0.6268	0.0214

Table 12: Granger Causality Test Results, India, p-values

	fin	bas	stap	prod	engy	hlth	ind	tech	tel	util
US	3-15,9	4-12,14-15,9	3-6,8-10,9	3-15,9	5-15,5	3-6,9-12,14-15,15	3-15,10	4,8-9,8	3-6,8-12,14-15,9	3-15,9
UK	3,5-6,10-15,6	5-14,5	5-11,14,6	3,6,6	2-15,3	5,6,6	3,5-6,10,14,6	3	5-15,5	5-6,8-15,6
CA	2-12,15,3	5-11,15,10	2-5,8-12,3	2-12,4	2-5,8-12,3	3	2-5,7-12	2-5,2	2-5,8-12,3	2-15,3
AU	1-6,12-15,15	3-12,14-15,3	1,3-7,13,4	7-15,9	3-6,3	1-7,9-14,2	3-15,15	3-4,6-15,7	1-6,3	1,3-5,12,15,3
DE	1-9,14,8	1-9,14,6	5	1,4-9,7	2-4,2	8-9,13-14,8	1,4-9,8	6-7,6	4-6,8-9,13-14,6	8,13-15,8
FR	5-9,6	1-7,12-14,3	5-6,6	6	6	1,3-6,5	2-11,6	3-9,15,6	12	1-2,4-9,6
IT	6-9,6	6-8,7	5-13,7	–	5-8,12-15,7	1-2,4-11,6	6-8,10-11,6	6-8,7	6-8,10-14,7	6-8,10-11,6
ES	5-9,11,6	1,4-9,11,6	10-15,11	9-11,10	1,5-9,10-11,14-15,7	5-6,9-11,14,11	5-13,15,8	5-13,5	4-15,6	5-9,11,6
CN	15	–	–	7-13,15,15	15	–	6-10,12,15,15	6-13,15,15	6-15,15	–
JP	12-15,13	12-15,13	13-14,14	10-15,12	12-14,13	–	10-15,13	11-15,14	12	–
IN	2-15,12	3-12,14,12	5,7-15,11	3-4,5-12,14,12	5-15,12	5-15,11	1-12,14,12	5,7,9-12,14-15,11	6,8-14,9	7-9,11-12,9

Note: The ranges or numbers indicate the lags at which Granger causality has been found statistically significant at the 90% confidence level or above. The last number in each cell indicates the lag at which the probability value to reject the null hypthesis of Granger noncausalit has been at its minimum.

Table 13: Granger Causality Test Results: Summary by Sector and Country

COVID-19 Cases and Stock Prices by Sector in Major Economies: What Do We Learn from the Daily Data?

Supplementary Online Appendix

Hussein Hassan, Minko Markovski and Alexander Mihailov

April 2022

Abstract

This appendix collects the same figures per country for the remaining six countries with a complete sectoral stock price index data set (i.e., all 11 GICS sectors) in our sample as for the five countries in the main text. It also adds univariate GARCH statistical significance tables for the six countries whose tables are not in the main text, to save space and keep focus there.

Contents

List of Figures

List of Tables

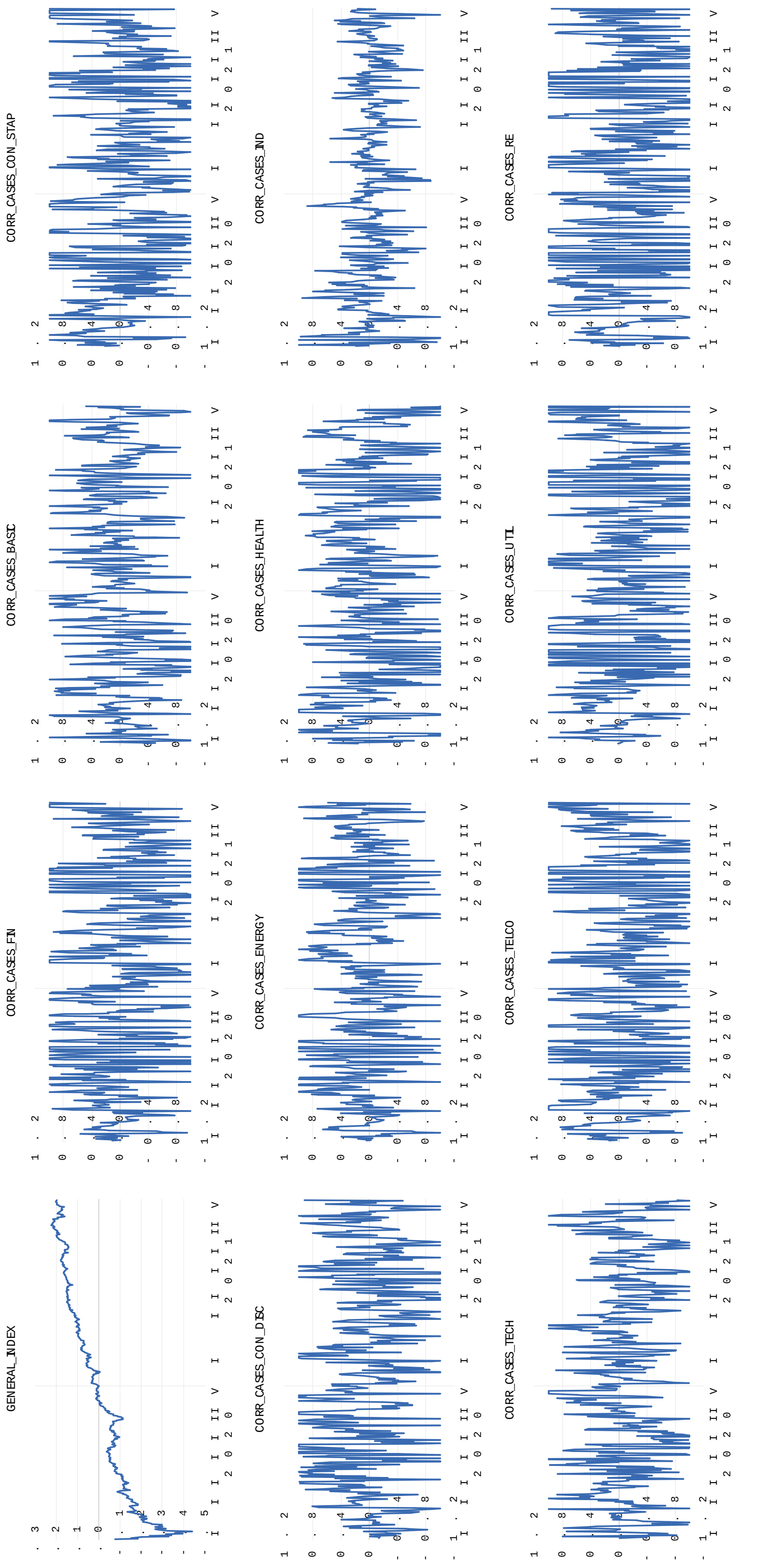

Figure 1: Canada – Estimated Daily Correlations between COVID-19 Cases and Sectoral Stock Price Indexes, Dynamics, 2020-2021

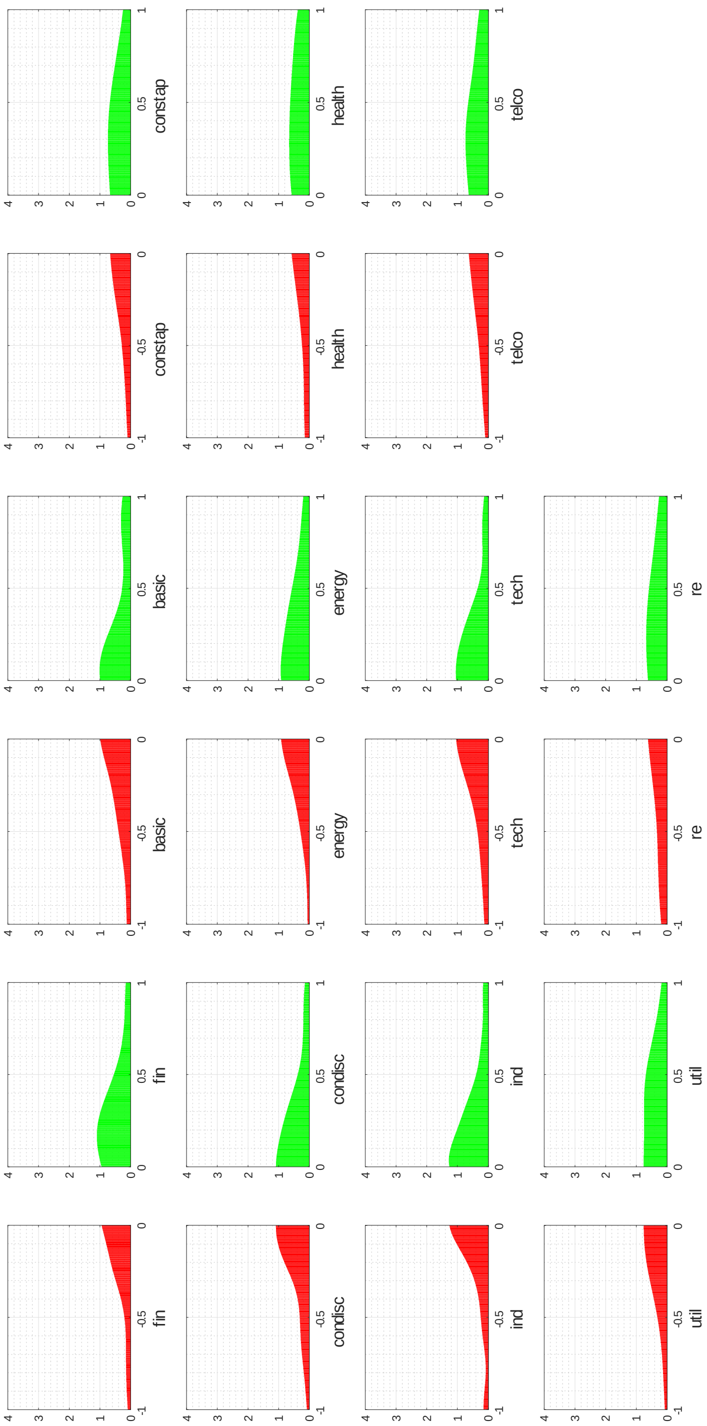

Figure 2: Canada – Estimated Daily Correlations between COVID-19 Cases and Sectoral Stock Price Indexes, Kernels, 2020 1st Half

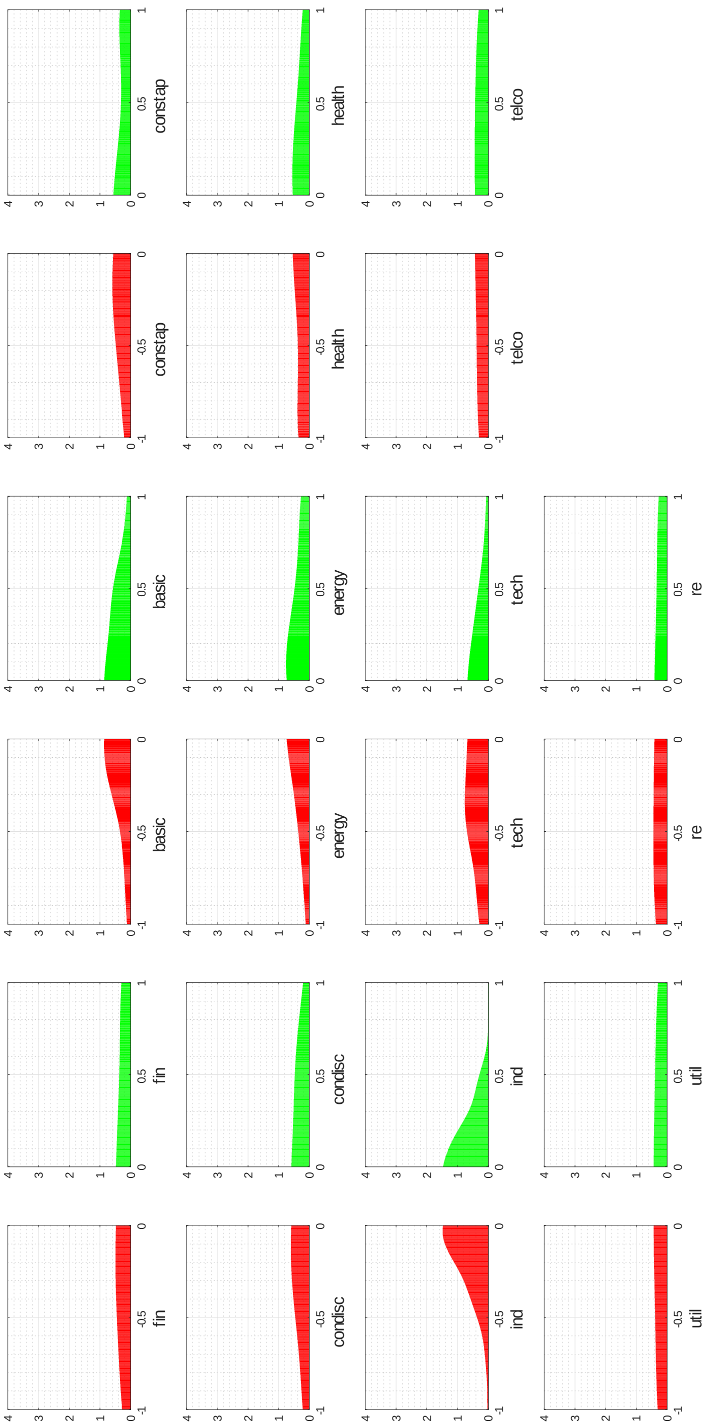

Figure 3: Canada – Estimated Daily Correlations between COVID-19 Cases and Sectoral Stock Price Indexes, Kernels, 2021 2nd Half

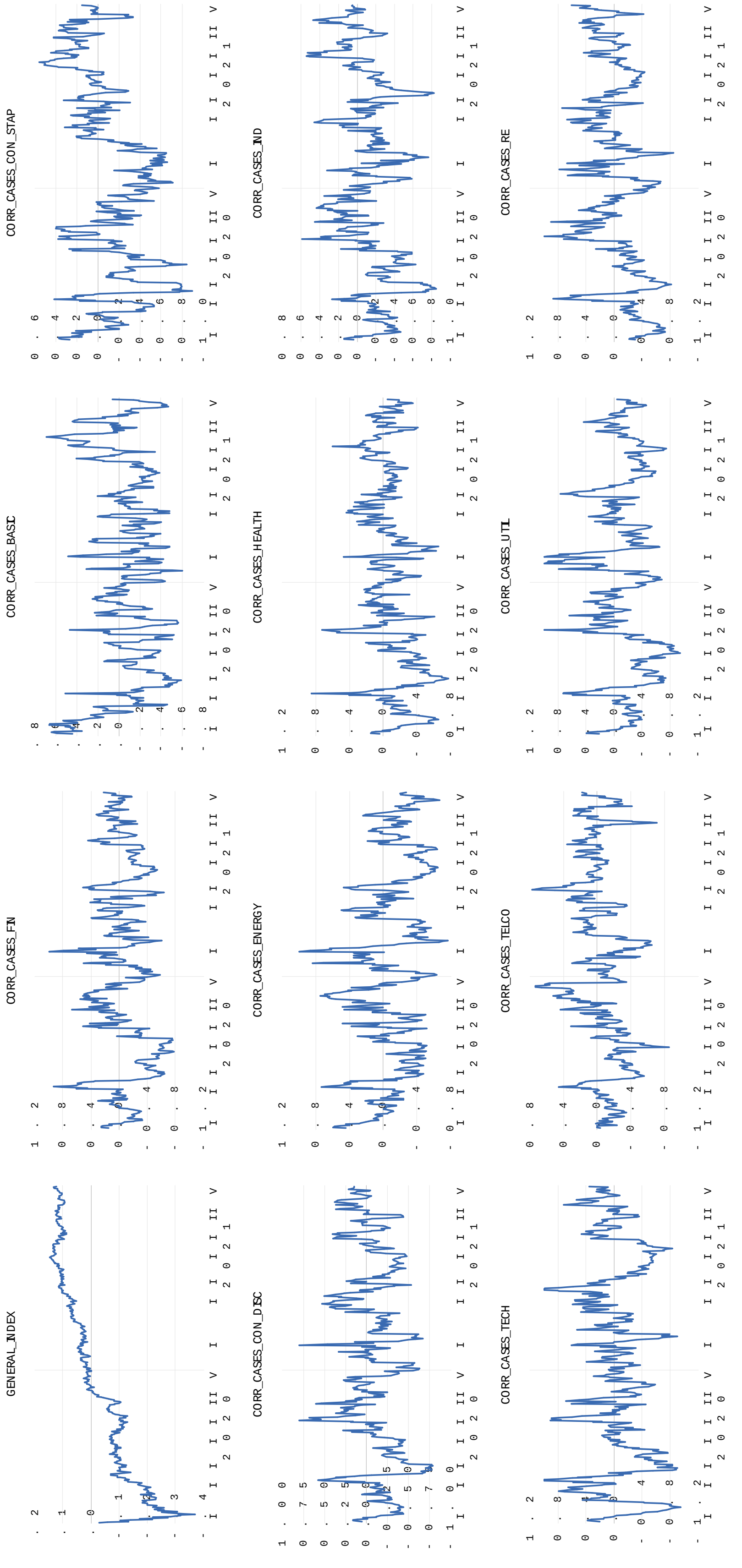

Figure 4: Australia – Estimated Daily Correlations between COVID-19 Cases and Sectoral Stock Price Indexes, Dynamics, 2020-2021

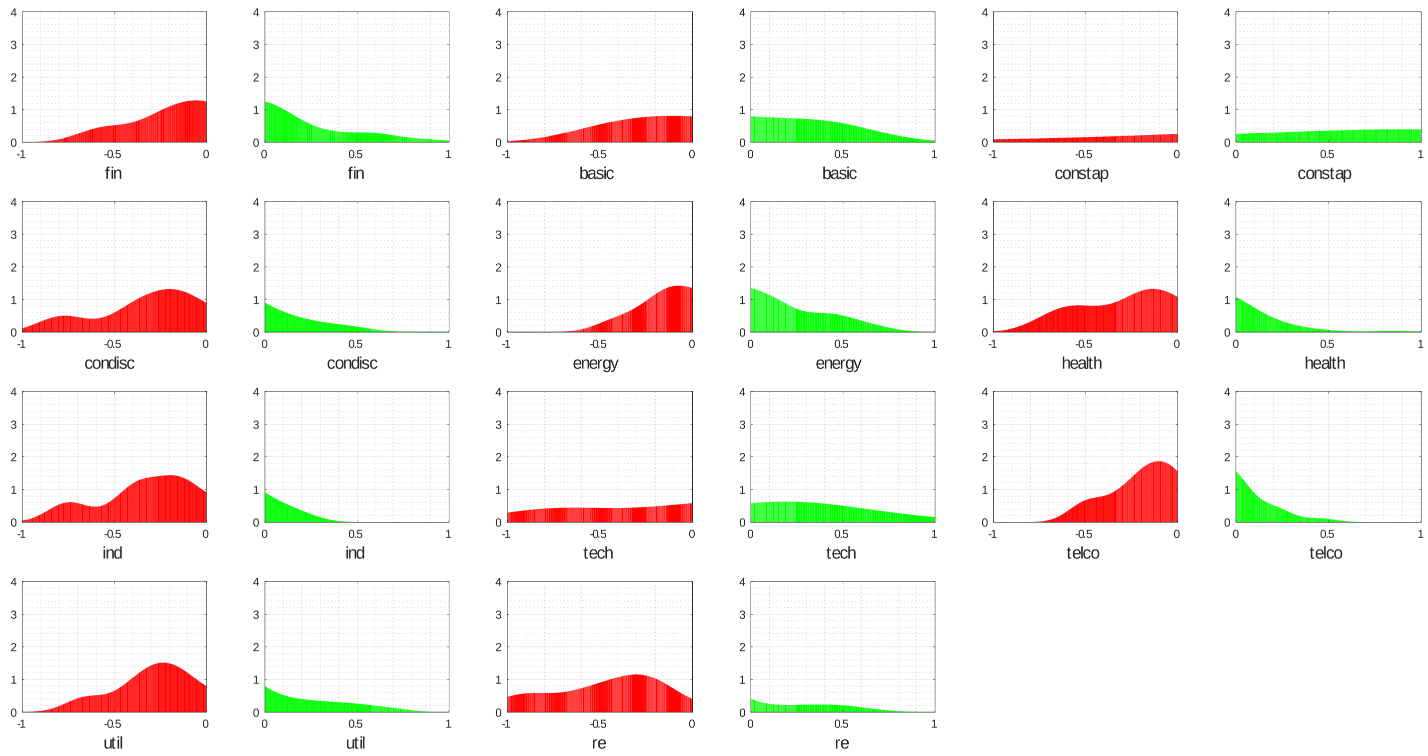

Figure 5: Australia – Estimated Daily Correlations between COVID-19 Cases and Sectoral Stock Price Indexes, Kernels, 2020 1st half (top two rows) and 2020 2nd half (bottom two rows)

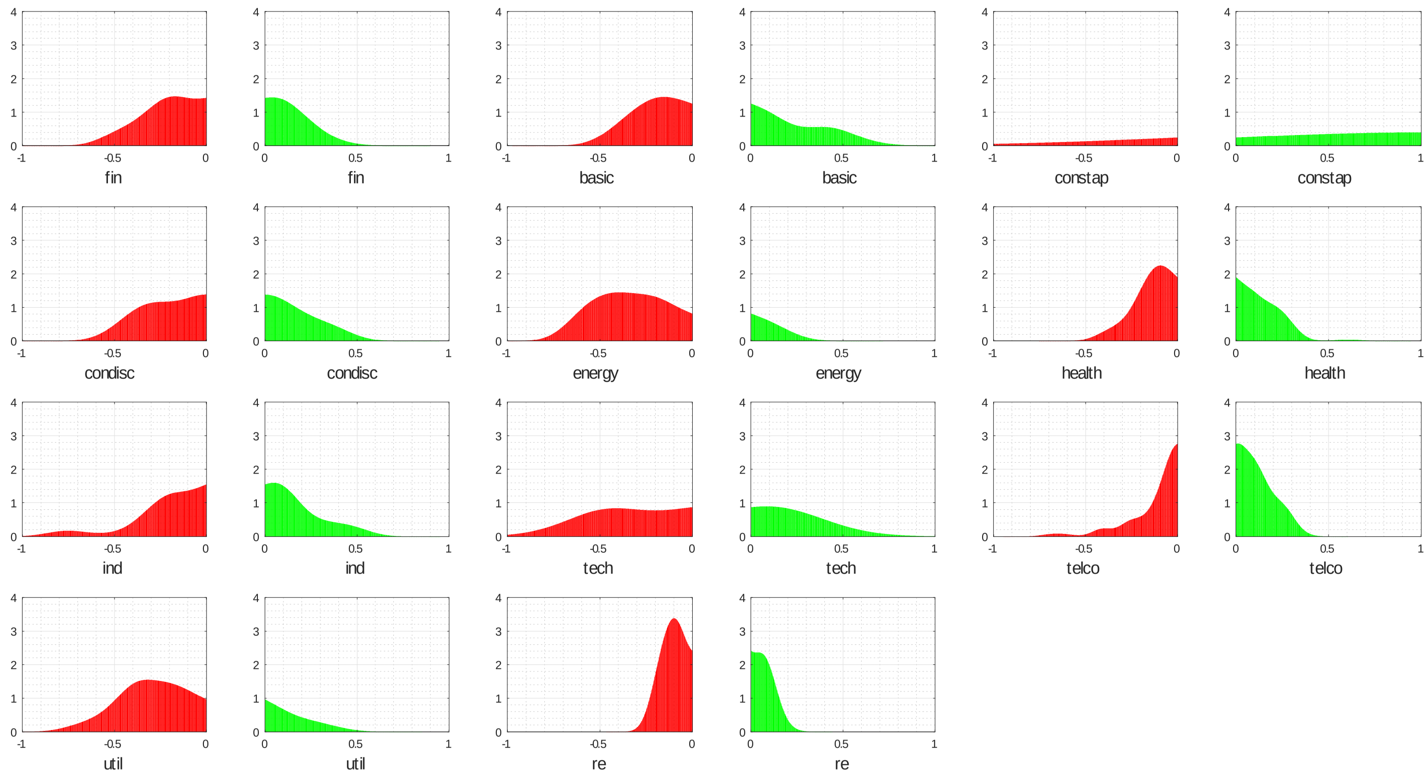

Figure 6: Australia – Estimated Daily Correlations between COVID-19 Cases and Sectoral Stock Price Indexes, Kernels, 2021 1st half (top two rows) and 2021 2nd half (bottom two rows)

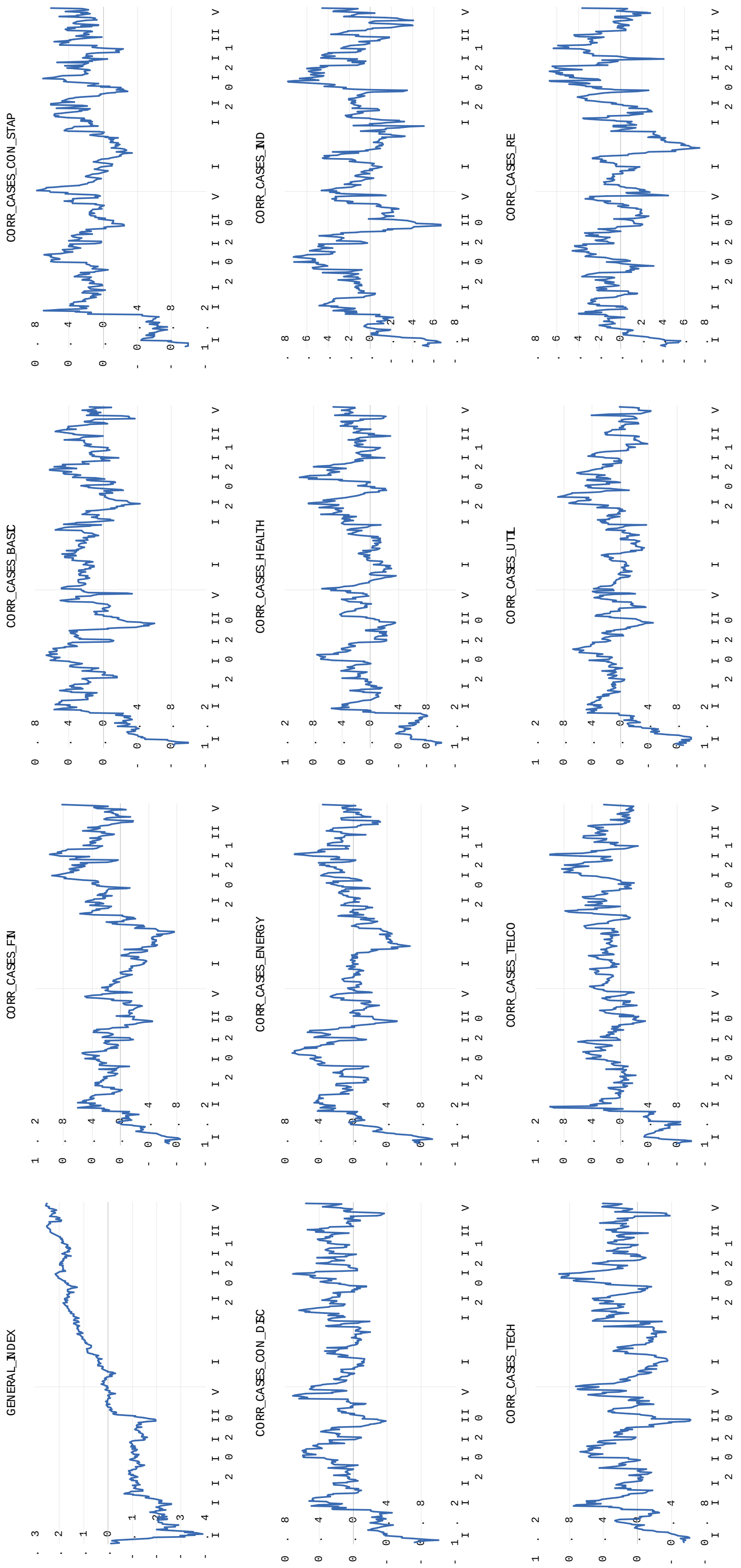

Figure 7: France – Estimated Daily Correlations between COVID-19 Cases and Sectoral Stock Price Indexes, Dynamics, 2020-2021

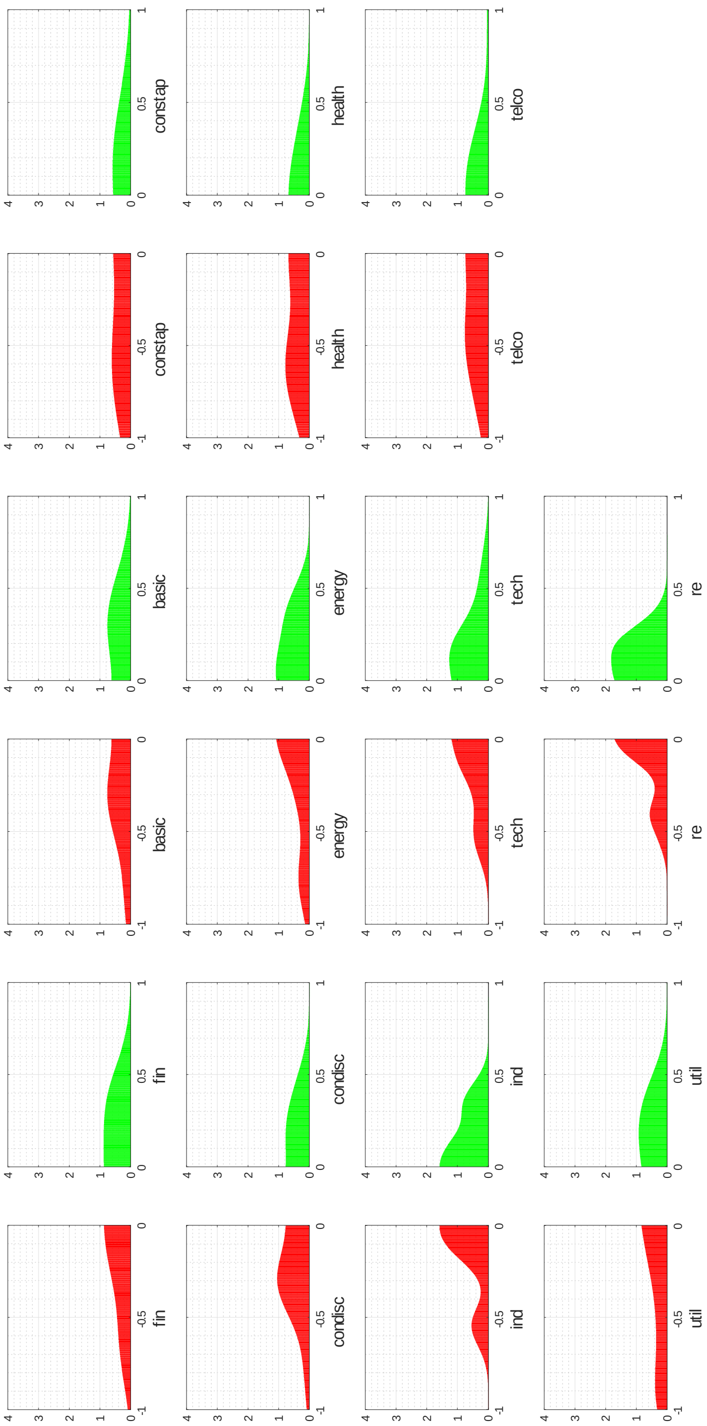

Figure 8: France – Estimated Daily Correlations between COVID-19 Cases and Sectoral Stock Price Indexes, Kernels, 2020 1st Half

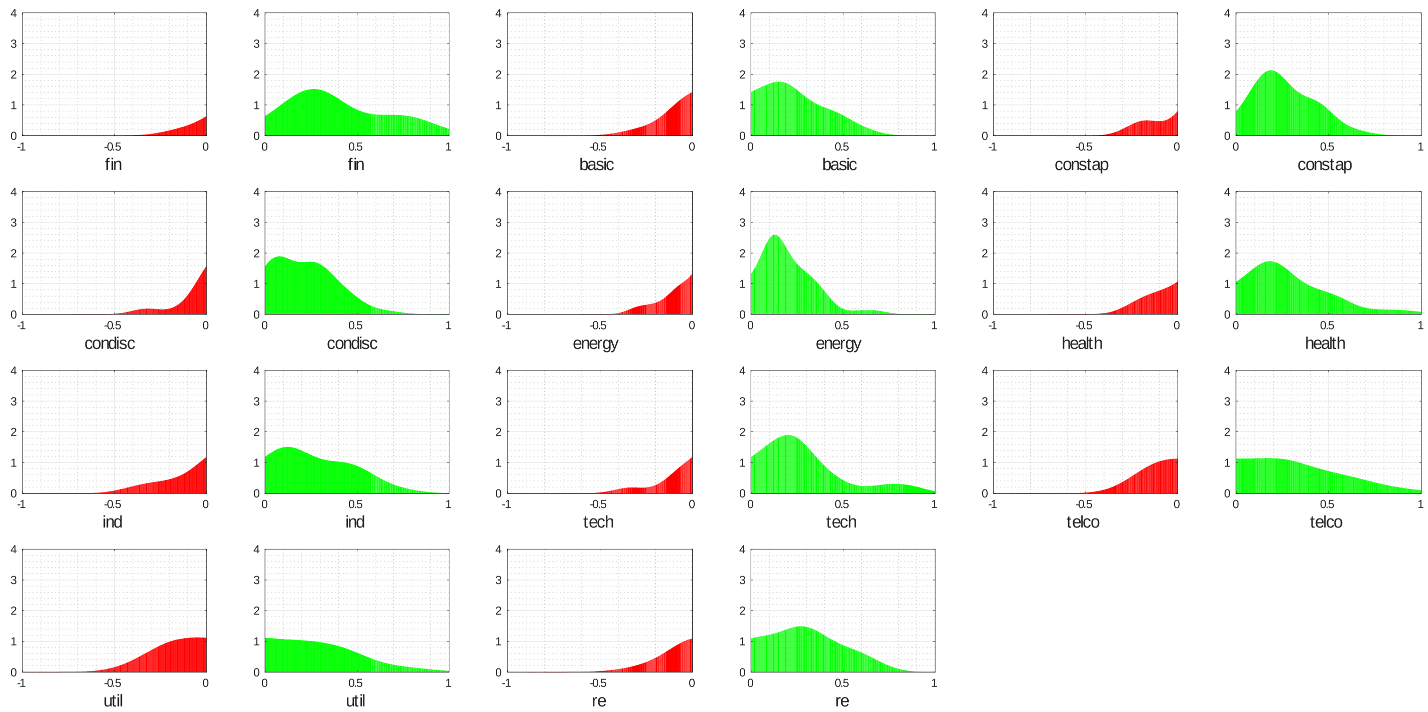

Figure 9: France – Estimated Daily Correlations between COVID-19 Cases and Sectoral Stock Price Indexes, Kernels, 2021 2nd Half

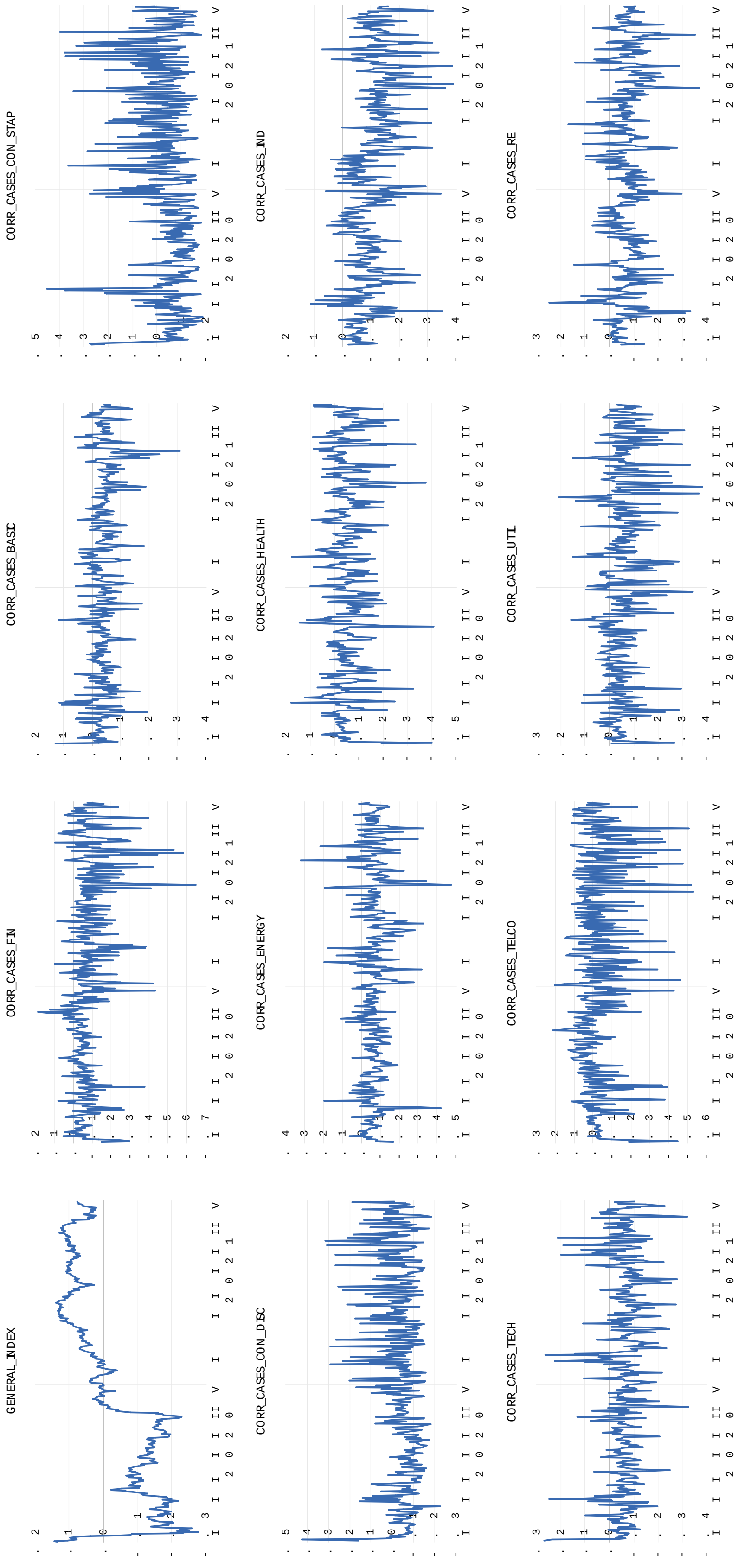

Figure 10: Spain – Estimated Daily Correlations between COVID-19 Cases and Sectoral Stock Price Indexes, Dynamics, 2020-2021

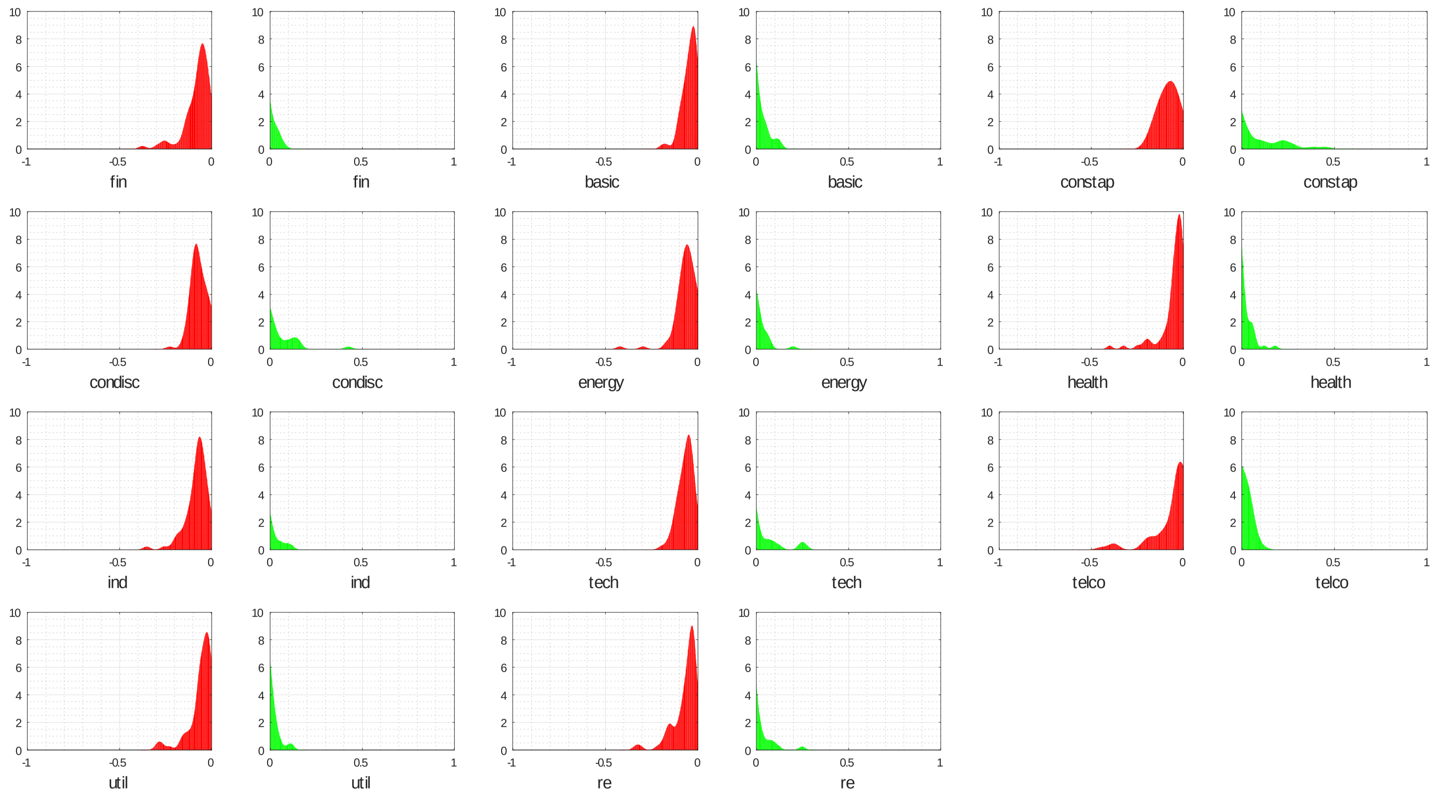

Figure 11: Spain – Estimated Daily Correlations between COVID-19 Cases and Sectoral Stock Price Indexes, Kernels, 2020 1st half (top two rows) and 2020 2nd half (bottom two rows)

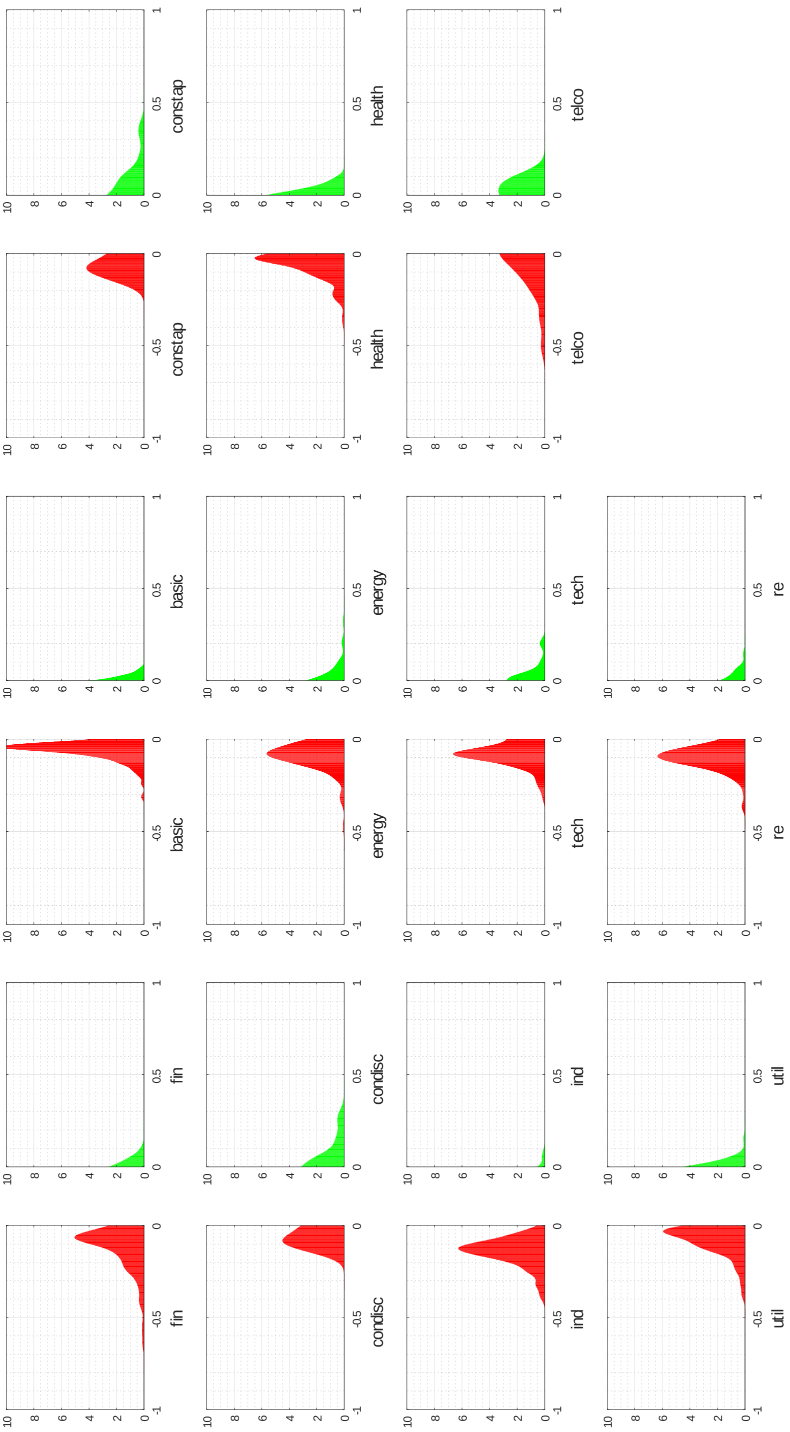

Figure 12: Spain – Estimated Daily Correlations between COVID-19 Cases and Sectoral Stock Price Indexes, Kernels, 2021 1st half (top two rows) and 2021 2nd half (bottom two rows)

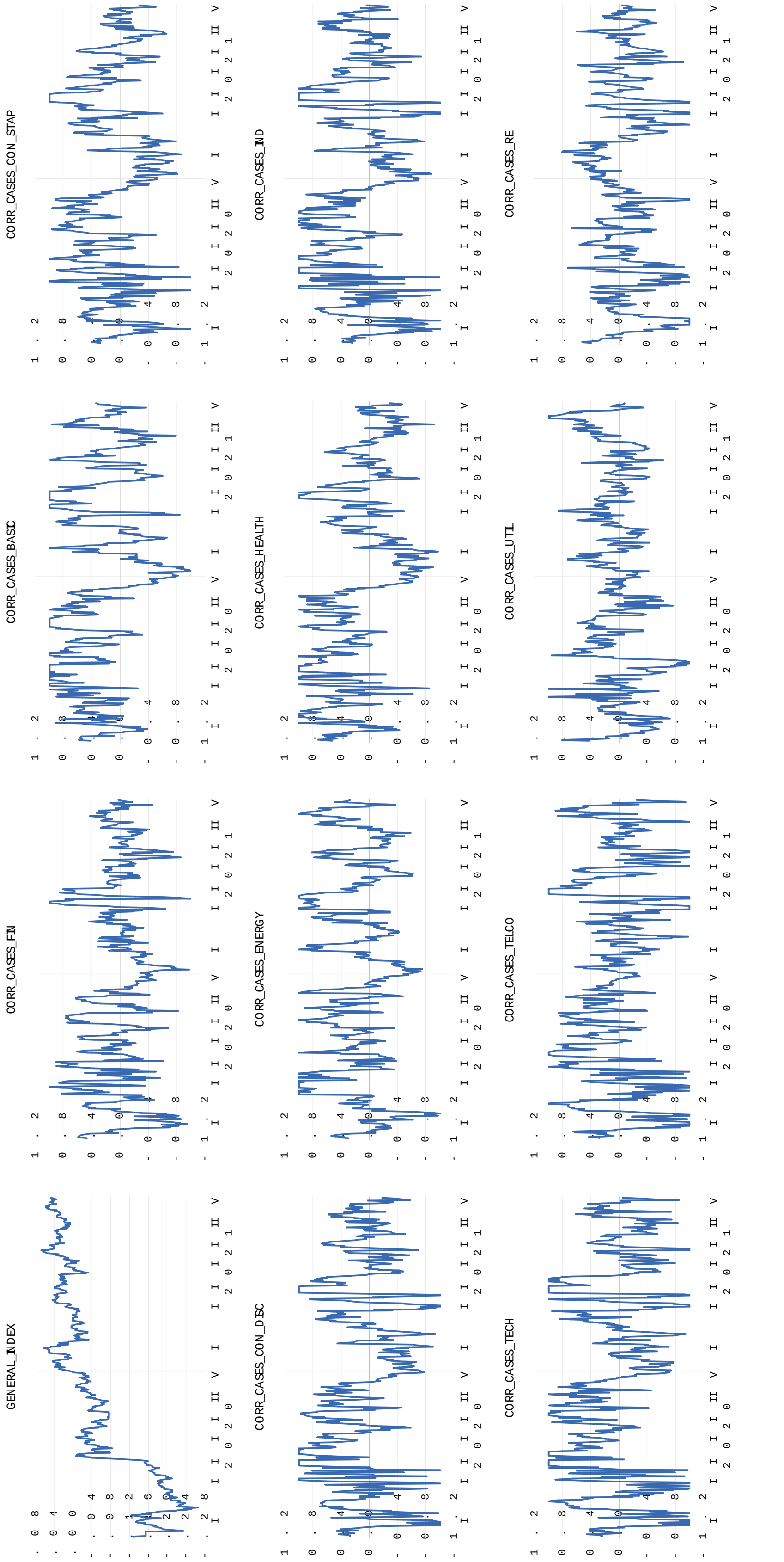

Figure 13: China – Estimated Daily Correlations between COVID-19 Cases and Sectoral Stock Price Indexes, Dynamics, 2020-2021

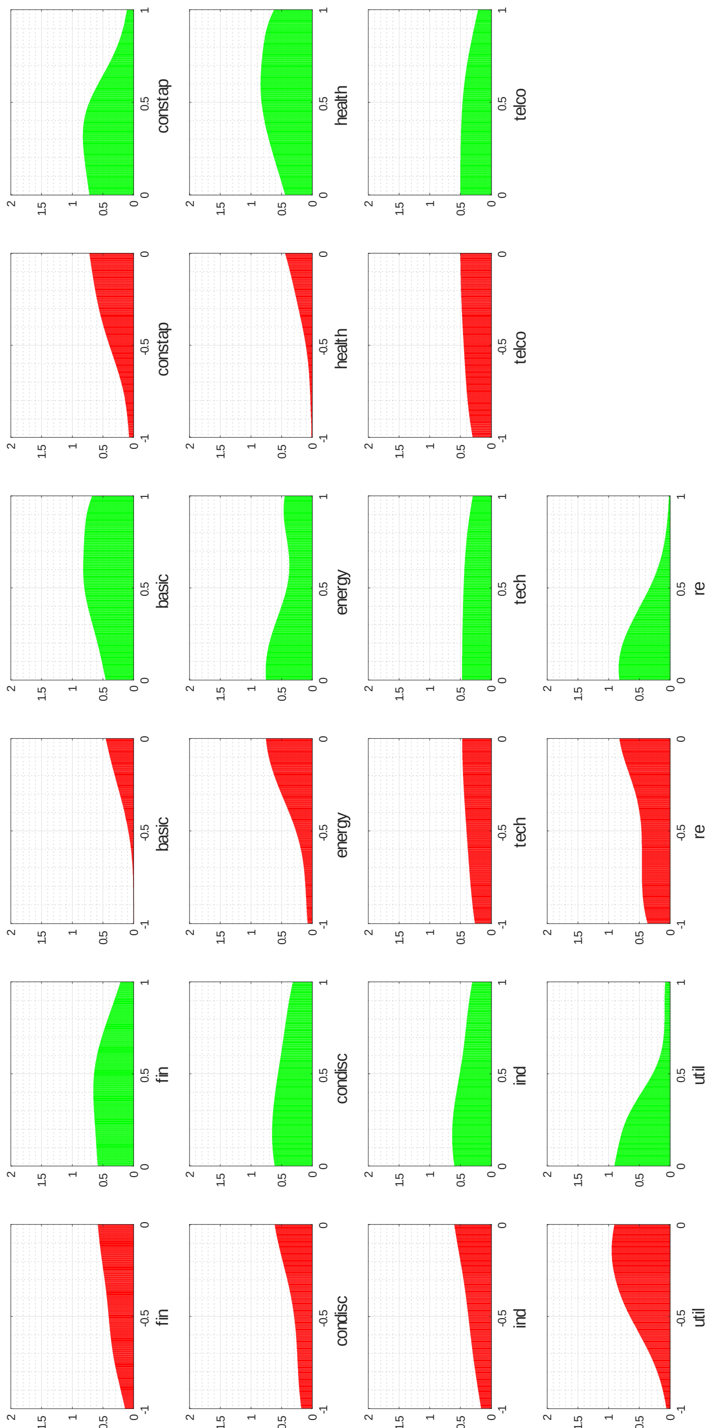

Figure 14: China – Estimated Daily Correlations between COVID-19 Cases and Sectoral Stock Price Indexes, Kernels, 2020 1st Half

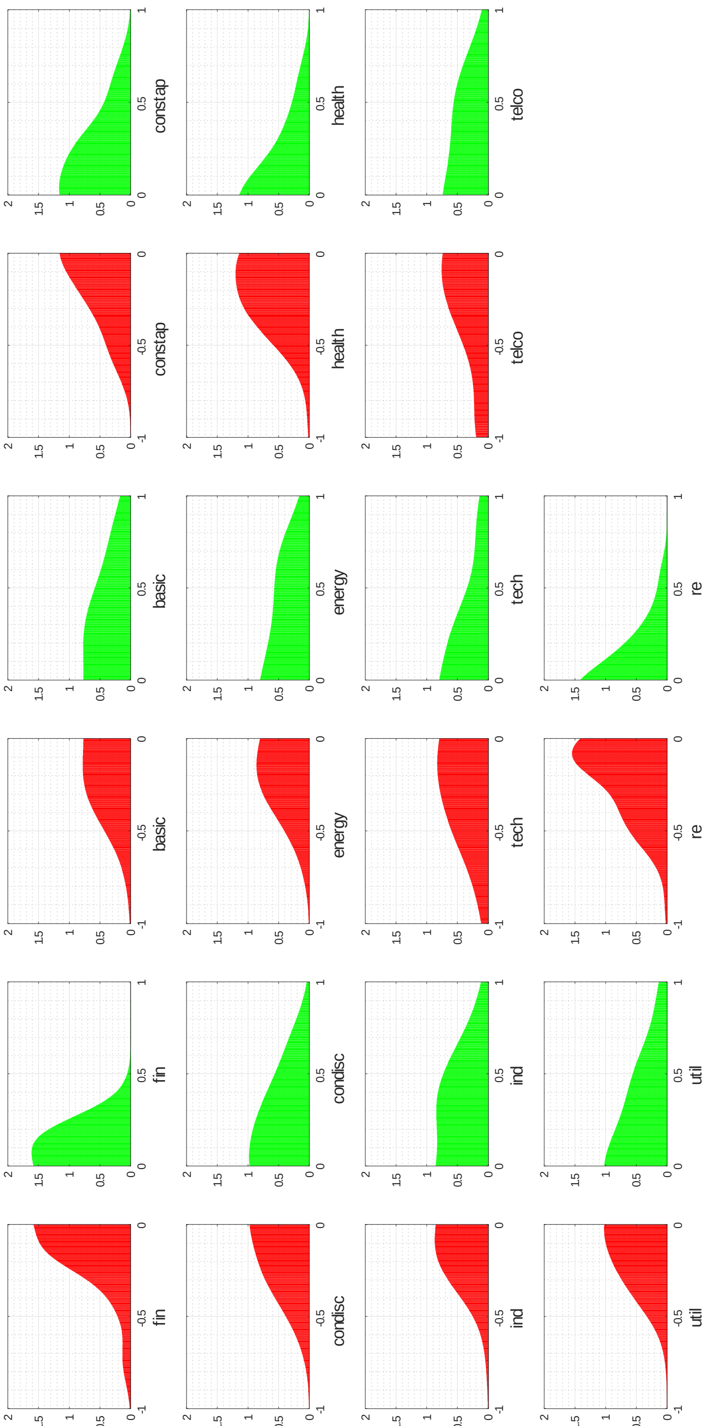

Figure 15: China – Estimated Daily Correlations between COVID-19 Cases and Sectoral Stock Price Indexes, Kernels, 2021 2nd Half

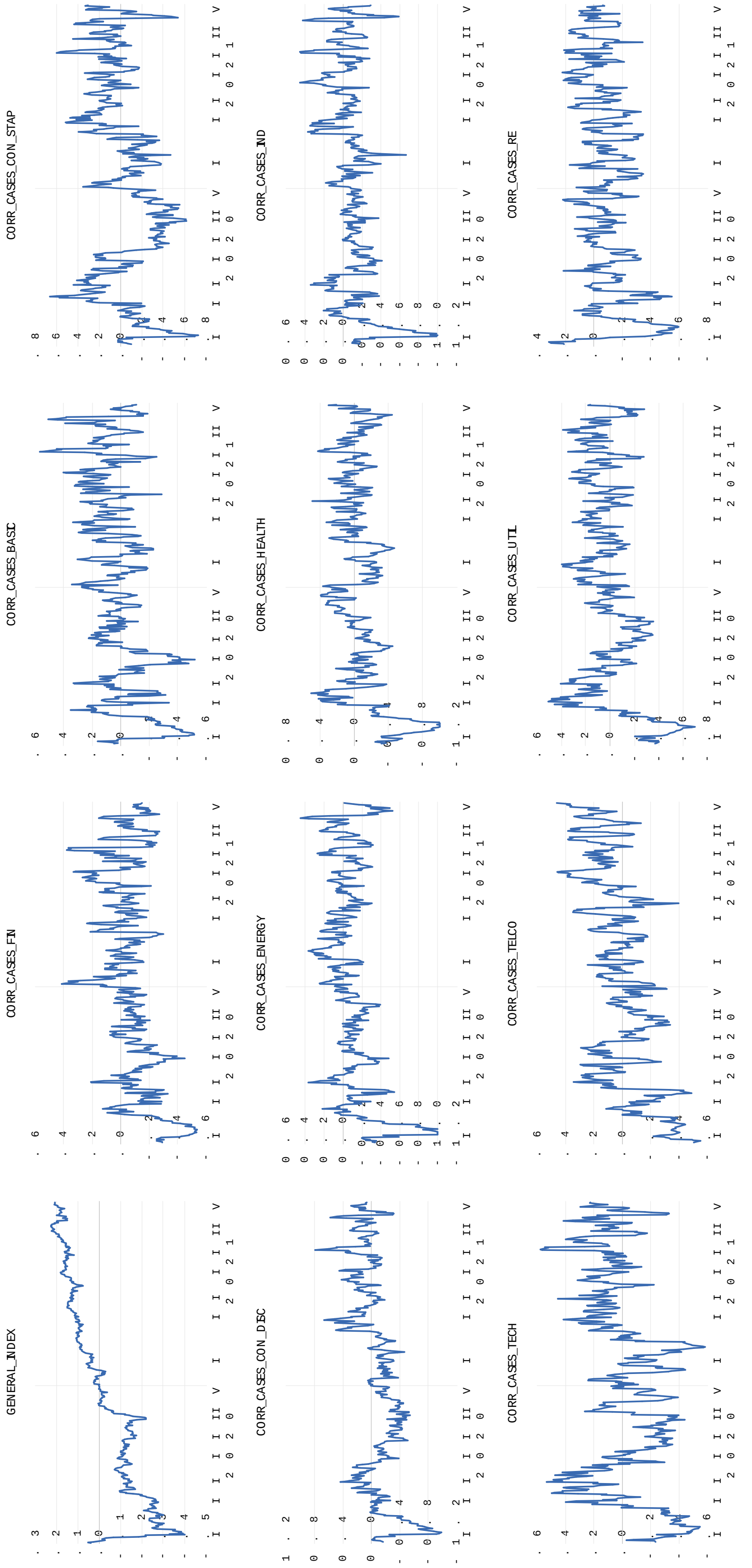

Figure 16: India – Estimated Daily Correlations between COVID-19 Cases and Sectoral Stock Price Indexes, Dynamics, 2020-2021

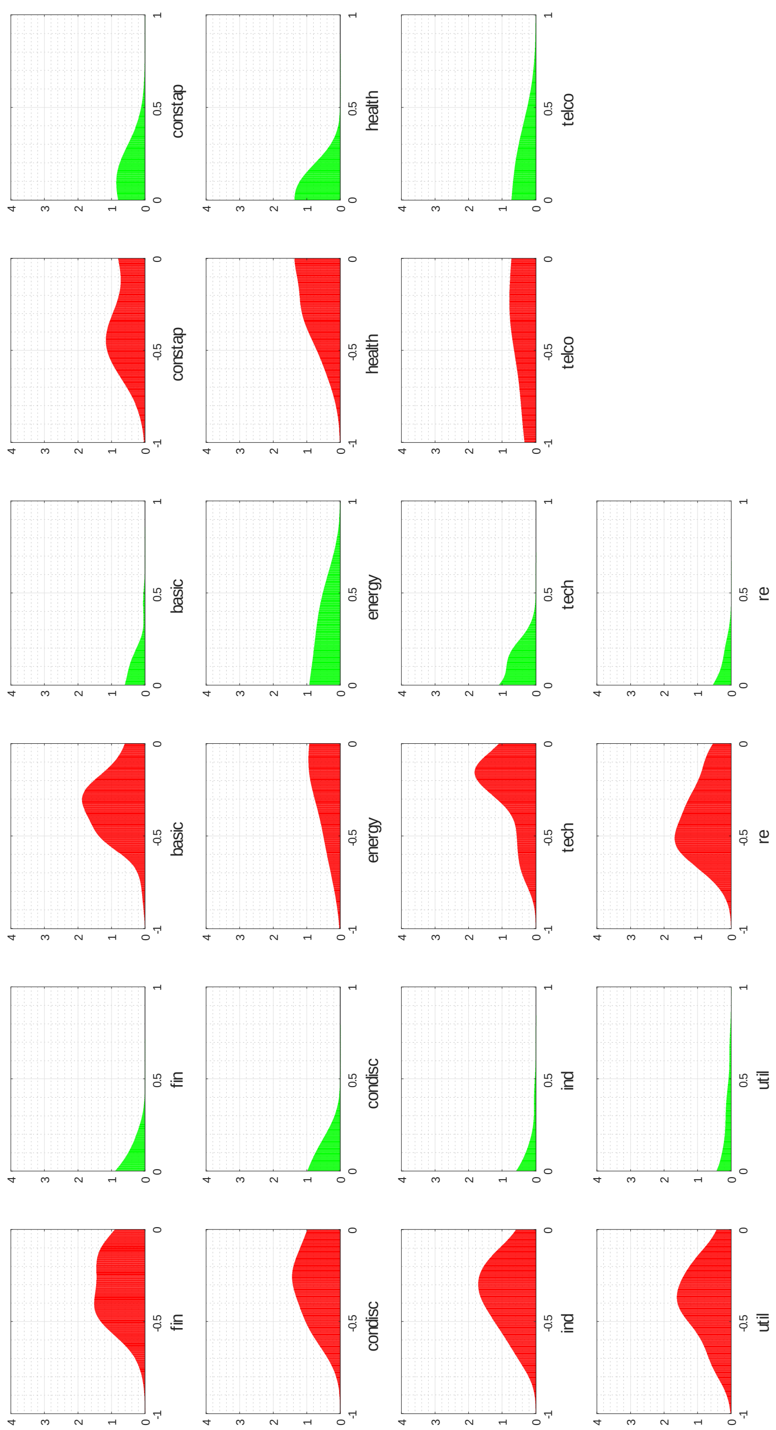

Figure 17: India – Estimated Daily Correlations between COVID-19 Cases and Sectoral Stock Price Indexes, Kernels, 2020 1st Half

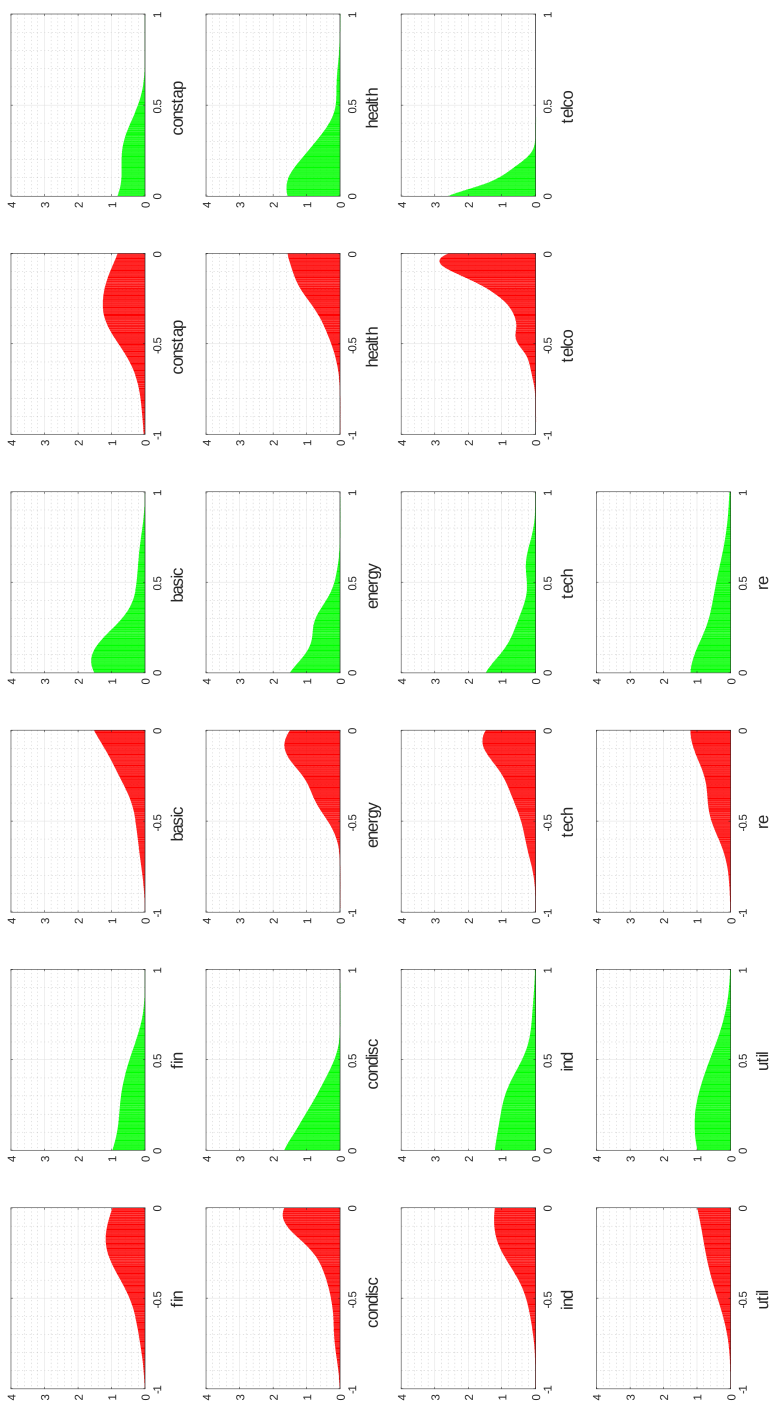

Figure 18: India – Estimated Daily Correlations between COVID-19 Cases and Sectoral Stock Price Indexes, Kernels, 2021 2nd Half

	ω	α	β	$\lvert\alpha+\beta\rvert$	F-LM
Individual Variables					
Basic	1.56E-05**	0.047134***	0.877597*	0.924731	1.75381
Bitcoin	0.000195*	0.086791*	0.799874*	0.886665	1.418127
Brent	2.42E-05***	0.333196*	0.693152*	1.026348	0.050606
COVID-19 Cases	8.64E-03*	0.530804*	0.48066*	1.011464	0.018412
Con. Disc	6.91E-06*	0.226856*	0.69856*	0.925416	0.519622
Con. Stap	4.37E-06*	0.121659*	0.800838*	0.922497	0.033795
Energy	1.27E-05*	0.075203*	0.860584*	0.935787	3.132883***
Financial	2.40E-06*	0.097254*	0.851442*	0.948696	0.242082
Exchange Rate	4.91E-07**	-0.00893	0.978238*	0.969306	0.866691
Gold	1.96E-05***	0.092198**	0.682897*	0.775095	0.830377
Health	3.35E-05**	0.126979*	0.823403*	0.950382	0.008733
Industrial	0.0000979	0.15	0.600000***	0.75	0.301213
Real Estate	3.64E-06*	0.128008*	0.826469*	0.954477	1.639458
Technology	2.12E-05***	0.064787**	0.885815*	0.950602	0.663872
Telco	2.03E-06*	0.187453*	0.779499*	0.966952	1.661105
Utility	1.60E-06*	0.072322*	0.878922*	0.951244	0.266422
Interest Rate	4.56E-15*	0.378494*	0.678025*	1.056519	0.003752
Summation Terms					
Basic	8.74E-03*	0.51858*	0.487603*	1.006183	0.054798
Bitcoin	1.02E-02*	0.498114*	0.486173*	0.984287	0.033019
Brent	9.62E-03*	0.495726*	0.49497*	0.990696	0.001904
Con. Disc	8.38E-03*	0.515338*	0.494381*	1.009719	0.009706
Con. Stap	8.08E-03*	0.512566*	0.498835*	1.011401	0.005929
Energy	8.49E-03*	0.507814*	0.500101*	1.007915	0.036855
Financial	8.24E-03*	0.510105*	0.499133*	1.009238	0.013053
Exchange Rate	8.67E-03*	0.535076*	0.476754*	1.01183	0.017879
Gold	8.65E-03*	0.53568*	0.477903*	1.013583	0.020867
Health	8.66E-03*	0.448814*	0.534614*	0.983428	0.006919
Industrial	8.69E-03*	0.520933*	0.485878*	1.006811	0.015687
Real Estate	7.82E-03*	0.487731*	0.518444*	1.006175	0.001255
Technology	9.08E-03*	0.519583*	0.482314*	1.001897	0.017619
Telco	8.03E-03*	0.503635*	0.505787*	1.009422	0.000982
Utility	8.11E-03*	0.504071*	0.504354*	1.008425	0.004937
Interest Rate	8.64E-03*	0.530806*	0.480659*	1.011465	0.018413

Note:
*, ** and *** denote the rejection of the null hypotheses at 1, 5 and 10%, respectively.
F-LM: ARCH test F-statistics for heteroskedasticity.

Table 1: Univariate GARCH Statistical Significance Test Results, CA

	ω	α	β	$\lvert\alpha+\beta\rvert$	F-LM
Individual Variables					
Basic	2.91E-05*	0.083053**	0.760455*	0.843508	2.534555
Bitcoin	1.78E-04*	0.067002**	0.827946*	0.894948	1.914259
Brent	1.88E-05**	0.237248*	0.762230*	0.999478	0.0000233
COVID-19 Cases	0.000462	0.128382*	0.877342*	1.005724	1.116228
Con. Disc	3.92E-06*	0.066047*	0.888141*	0.954188	0.158009
Con. Stap	8.75E-06*	0.106091*	0.805543*	0.911634	0.385265
Energy	7.70E-06*	0.034503**	0.908954*	0.943457	2.902838***
Financial	3.34E-06*	0.091357*	0.867047*	0.958404	0.38531
Exchange Rate	8.79E-07*	0.000128	0.967924*	0.968052	0.002701
Gold	5.47E-06*	-0.00078	0.934976*	0.934194	0.008227
Health	6.28E-06*	0.045783**	0.901476*	0.947259	1.396287
Industrial	3.02E-06**	0.058185**	0.906986*	0.965171	0.024065
Real Estate	3.81E-06*	0.070479*	0.890312*	0.960791	0.083952
Technology	2.82E-05*	0.006512	0.889271*	0.895783	0.0000139
Telco	1.48E-06*	-0.01573**	0.994366*	0.978634	0.064864
Utility	2.83E-06**	0.033684***	0.933412*	0.967096	0.616409
Interest Rate	2.1E-13	0.15	0.6**	0.75	1.869922
Summation Terms					
Basic	0.000494	0.129274*	0.876147*	1.005421	1.125056
Bitcoin	0.000681	0.118149*	0.883607*	1.001756	1.685712
Brent	0.00046	0.127636*	0.87728*	1.004916	0.999
Con. Disc	0.000487	0.130147*	0.875684*	1.005831	1.352787
Con. Stap	0.000496	0.127677*	0.877578*	1.005255	1.244878
Energy	0.000461	0.131612*	0.874431*	1.006043	1.38318
Financial	0.000478	0.130472*	0.875519*	1.005991	1.373933
Exchange Rate	0.000469	0.127354*	0.878071*	1.005425	1.080167
Gold	0.000472	0.128535*	0.877293*	1.005828	1.11279
Health	0.000499	0.130459*	0.875283*	1.005742	1.257646
Industrial	0.000485	0.128978*	0.876644*	1.005622	1.297394
Real Estate	0.000494	0.132188*	0.874238*	1.006426	1.380281
Technology	0.000488	0.136687*	0.870311*	1.006998	1.230067
Telco	0.000486	0.128719*	0.87688*	1.005599	1.409063
Utility	0.000451	0.13226*	0.874255*	1.006515	1.355833
Interest Rate	0.000462	0.128382*	0.877342*	1.005724	1.12

Note:

*, ** and *** denote the rejection of the null hypotheses at 1, 5 and 10%, respectively.

F-LM: ARCH test F-statistics for heteroskedasticity.

Table 2: Univariate GARCH Statistical Significance Test Results, AU

	ω	α	β	$\|\alpha+\beta\|$	F-LM
Individual Variables					
Basic	4.38E-06*	0.130537*	0.82749*	0.958027	0.271206
Bitcoin	8.19E-05*	0.043419*	0.909715*	0.953134	0.789161
Brent	2.22E-05*	0.338076*	0.699072*	1.037148	0.0000308
COVID-19 Cases	0.00949	0.103208*	0.889899*	0.993107	0.144392
Con. Disc	1.39E-05*	0.24079*	0.702698*	0.943488	0.085918
Con. Stap	5.42E-06**	0.166505*	0.783771*	0.950276	0.216056
Energy	7.15E-06*	0.042803*	0.925674*	0.968477	0.009378
Financial	5.57E-06**	0.068778*	0.902569*	0.971347	0.045508
Exchange Rate	4.57E-07***	0.03838***	0.920883*	0.959263	0.076676
Gold	1.61E-05**	0.138826*	0.693554*	0.83238	1.215126
Health	3.71E-06***	0.115995*	0.843536*	0.959531	0.166117
Industrial	4.54E-06*	0.035766*	0.93121*	0.966976	0.039925
Real Estate	6.54E-06*	0.143021*	0.821036*	0.964057	1.166737
Technology	6.31E-06**	0.056801**	0.898989*	0.95579	0.707334
Telco	4.21E-06***	0.465054*	0.623209*	1.088263	0.177361
Utility	1.82E-06*	-0.02287*	1.006457*	0.983583	2.380018
Interest Rate	3.66E-15	0.554184*	0.680251*	1.234435	0.557504
Summation Terms					
Basic	0.00964	0.103249*	0.889687*	0.992936	0.159599
Bitcoin	0.00936	0.111604*	0.883627*	0.995231	0.157183
Brent	0.00904	0.1027*	0.89166*	0.99436	0.175551
Con. Disc	0.0095	0.103906*	0.889424*	0.99333	0.166442
Con. Stap	0.00945	0.103997*	0.889419*	0.993416	0.164344
Energy	0.0092	0.10363*	0.890349*	0.993979	0.205785
Financial	0.00914	0.104538*	0.889661*	0.994199	0.209617
Exchange Rate	0.00957	0.103097*	0.889817*	0.992914	0.1367
Gold	0.00951	0.102954*	0.890069*	0.993023	0.138792
Health	0.00948	0.104146*	0.889222*	0.993368	0.157279
Industrial	0.00951	0.103813*	0.88949*	0.993303	0.19856
Real Estate	0.00927	0.102934*	0.890666*	0.9936	0.193511
Technology	0.00953	0.104552*	0.888802*	0.993354	0.189694
Telco	0.00966	0.103675*	0.889255*	0.99293	0.134294
Utility	0.00942	0.103718*	0.889774*	0.993492	0.200315
Interest Rate	0.00949	0.103208*	0.889899*	0.993107	0.144394

Note:
*, ** and *** denote the rejection of the null hypotheses at 1, 5 and 10%, respectively.
F-LM: ARCH test F-statistics for heteroskedasticity.

Table 3: Univariate GARCH Statistical Significance Test Results, FR

	ω	α	β	$\lvert\alpha+\beta\rvert$	F-LM
Individual Variables					
Basic	0.000189	0.15	0.600000***	0.75	0.84
Bitcoin	5.35E-05**	0.062548*	0.906584*	0.969132	1.18
Brent	1.77E-05***	0.314703*	0.714770*	1.029473	0.000000439
COVID-19 Cases	1.19E-01*	-0.065593**	0.488678*	0.423085	3.24E+00***
Con. Disc	3.22E-05*	0.295088*	0.655313*	0.950401	0.0244
Con. Stap	1.86E-05*	0.252044*	0.551438*	0.803482	0.0374
Energy	3.72E-06*	-0.020968*	1.003321*	0.982353	0.0337
Financial	0.00000109	-0.015769*	1.008786*	0.993017	2.35
Exchange Rate	1.04E-07*	-0.016435***	1.004981*	0.988546	0.00733
Gold	4.67E-06***	0.011848	0.931089*	0.942937	0.121
Health	5.62E-06**	0.025081***	0.939319*	0.9644	0.0474
Industrial	9.41E-06*	0.137080*	0.813182*	0.950262	0.154
Real Estate	2.92E-06**	0.103177*	0.844285*	0.947462	0.31
Technology	2.54E-06**	-0.015948*	1.007388*	0.99144	1.4
Telco	1.27E-05*	0.099456*	0.815231*	0.914687	0.0372
Utility	1.20E-05*	0.159678*	0.756993*	0.916671	0.0594
Interest Rate	2.11E-14***	0.822722*	0.522653*	1.345375	0.000381
Summation Terms					
Basic	1.19E-01*	-0.065935**	0.490429*	0.424494	3.14E+00***
Bitcoin	1.22E-01*	-0.064563**	0.479981*	0.415418	2.78E+00***
Brent	1.18E-01*	-0.067718**	0.497583*	0.429865	2.95E+00***
Con. Disc	1.19E-01*	-0.062354**	0.486557*	0.424203	3.19E+00***
Con. Stap	1.19E-01*	-0.063262**	0.485158*	0.421896	3.08E+00***
Energy	1.19E-01*	-0.064774**	0.485700*	0.420926	3.00E+00***
Financial	1.19E-01*	-0.068039**	0.488230*	0.420191	3.44E+00***
Exchange Rate	1.19E-01*	-0.066379**	0.491035*	0.424656	3.30E+00***
Gold	1.21E-01*	-0.064717**	0.480940*	0.416223	3.05E+00***
Health	1.20E-01*	-0.065830**	0.482396*	0.416566	3.19E+00***
Industrial	1.18E-01*	-0.066105**	0.490239*	0.424134	3.11E+00***
Real Estate	1.19E-01*	-0.065701**	0.487243*	0.421542	3.23E+00***
Technology	1.17E-01*	-0.064863**	0.496886*	0.432023	3.16E+00***
Telco	1.20E-01*	-0.069028**	0.485867*	0.416839	3.23E+00***
Utility	1.19E-01*	-0.066795**	0.487970*	0.421175	3.33E+00***
Interest Rate	1.19E-01*	-0.065593**	0.488678*	0.423085	3.24E+00***

Notes:

*, ** and *** denote the rejection of the null hypotheses at 1, 5 and 10%, respectively.

F-LM: ARCH test F-statistics for heteroskedasticity.

Table 4: Univariate GARCH Statistical Significance Test Results, ES

	ω	α	β	$\lvert\alpha+\beta\rvert$	F-LM
Individual Variables					
Basic	1.22E-05**	0.109181**	0.848516*	0.957697	0.032491
Bitcoin	1.03E-04**	0.245867*	0.760949*	1.006816	0.765615
Brent	2.38E-05**	0.307124*	0.717488*	1.024612	1.28846
COVID-19 Cases	0.00332	0.251253*	0.773344*	1.024597	0.093444
Con. Disc	7.04E-06***	0.039791**	0.92152*	0.961311	0.763976
Con. Stap	1.63E-05***	0.061903*	0.880171*	0.942074	0.05835
Energy	3.94E-06**	0.120814*	0.865356*	0.98617	0.830984
Financial	1.33E-05*	0.211055*	0.706722*	0.917777	0.218858
Exchange Rate	-1.56E-08**	0.001495	0.999017*	1.000512	0.796416
Gold	9.27E-06**	0.062547**	0.844122*	0.906669	0.997689
Health	0.0000155	0.065315*	0.887569*	0.952884	1.973405
Industrial	4.24E-06**	0.054339*	0.908742*	0.963081	0.558969
Real Estate	9.62E-06**	0.069562*	0.893099*	0.962661	0.316052
Technology	0.00000322	0.028438**	0.955984*	0.984422	0.069684
Telco	0.000000233	-0.00946	1.00446*	0.995004	0.202203
Utility	4.23E-06**	0.175974*	0.813574*	0.989548	0.236538
Interest Rate	2.95E-13*	0.367387*	0.66141*	1.028797	0.323117
Summation Terms					
Basic	0.00273	0.250397*	0.779674*	1.030071	0.062267
Bitcoin	0.00317	0.257994*	0.76869*	1.026684	0.038128
Brent	0.00311	0.247759*	0.777986*	1.025745	0.098441
Con. Disc	0.00287	0.242276*	0.78372*	1.025996	0.056902
Con. Stap	0.00293	0.247561*	0.779142*	1.026703	0.043629
Energy	0.00307	0.254003*	0.77388*	1.027883	0.074879
Financial	0.00307	0.24761*	0.777515*	1.025125	0.071487
Exchange Rate	0.00335	0.251921*	0.772654*	1.024575	0.097312
Gold	0.00317	0.248957*	0.77593*	1.024887	0.082015
Health	0.00275	0.248015*	0.78032*	1.028335	0.063088
Industrial	0.00298	0.243822*	0.781785*	1.025607	0.061091
Real Estate	0.00349	0.245477*	0.776153*	1.02163	0.108025
Technology	0.00269	0.234551*	0.790453*	1.025004	0.064308
Telco	0.00301	0.236505*	0.786336*	1.022841	0.052496
Utility	0.00333	0.251126*	0.773566*	1.024692	0.102467
Interest Rate	0.00332	0.251253*	0.773345*	1.024598	0.093437

Notes:
*, ** and *** denote the rejection of the null hypotheses at 1, 5 and 10%, respectively.
F-LM: ARCH test F-statistics for heteroskedasticity.

Table 5: Univariate GARCH Statistical Significance Test Results, CN

	ω	α	β	$\lvert\alpha+\beta\rvert$	F-LM
Individual Variables					
Basic	9.91E-06*	0.005401	0.939199*	0.9446	0.017342
Bitcoin	1.67E-04*	0.04187**	0.858371*	0.900241	2.240266
Brent	2.28E-05**	0.268284*	0.729982*	0.998266	0.152677
COVID-19 Cases	0.000338	0.157722*	0.832222*	0.989944	0.048233
Con. Disc	3.87E-06**	0.07211*	0.899736*	0.971846	0.381769
Con. Stap	3.51E-06*	0.062933**	0.87924*	0.942173	0.11932
Energy	9.28E-06*	0.034416**	0.916738*	0.951154	0.214459
Financial	0.0000032	0.066398	0.911557	0.977955	0.354589
Exchange Rate	2.12E-07*	-0.00414	0.976005*	0.971867	2.251263
Gold	0.00000507	0.00232	0.937268*	0.939588	0.225159
Health	7.59E-06*	0.022177	0.904499*	0.926676	1.854448
Industrial	3.93E-06*	0.034085**	0.927286*	0.961371	0.859736
Real Estate	1.39E-05**	0.023083	0.930205*	0.953288	0.950769
Technology	4.48E-06*	0.037149**	0.928969*	0.966118	1.119201
Telco	0.000237	0.15	0.6	0.75	0.766483
Utility	0.0000129	-0.012532	0.934765	0.922233	0.243442
Interest Rate	2.61E-12	0.15	0.600000**	0.75	0.00111
Summation Terms					
Basic	0.000327	0.162360*	0.829114*	0.991474	0.001569
Bitcoin	0.000428	0.150966*	0.837135*	0.988101	0.467313
Brent	0.000348	0.149781*	0.840585*	0.990366	0.03999
Con. Disc	0.00034	0.154068*	0.835306*	0.989374	0.047377
Con. Stap	0.000345	0.156060*	0.832987*	0.989047	0.007695
Energy	0.000394	0.149032*	0.837117*	0.986149	0.016131
Financial	0.000334	0.154767*	0.834753*	0.98952	0.025017
Exchange Rate	0.00034	0.156799*	0.832877*	0.989676	0.122586
Gold	0.000362	0.158486*	0.830484*	0.98897	0.001771
Health	0.000352	0.156990*	0.832442*	0.989432	0.000013
Industrial	0.000324	0.161671*	0.829495*	0.991166	0.054
Real Estate	0.000344	0.157488*	0.832357*	0.989845	0.127
Technology	0.000338	0.155466*	0.834109*	0.989575	0.0146
Telco	0.000401	0.146484*	0.838575*	0.985059	0.0705
Utility	0.000323	0.167796*	0.823950*	0.991746	0.000829
Interest Rate	0.000338	0.157722*	0.832222*	0.989944	0.0482

Notes:
*, ** and *** denote the rejection of the null hypotheses at 1, 5 and 10%, respectively.
F-LM: ARCH test F-statistics for heteroskedasticity.

Table 6: Univariate GARCH Statistical Significance Test Results, IN