Financial Earthquakes: SARS-CoV-2 News Shock Propagation in Stock and Sovereign Bond Markets

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Abstract

The SARS-CoV-2 epidemics outbreak has shocked global financial markets, inducing policymakers to put in place unprecedented interventions to inject liquidity and to counterbalance the negative impact on worldwide financial systems. Through the lens of statistical physics, we examine the financial volatility of the reference stock and bond markets of the United States, United Kingdom, Spain, France, Germany and Italy to quantify the effects of country-specific socio-economic and political announcements related to the epidemics. Main results show that financial markets exhibit heterogeneous behaviours towards news on the epidemics, with the Italian and German bond markets responding with major delays to shocks. Additionally, credit markets tend to be slower than equity markets in adjusting prices after shocks, hence being slower at incorporating the effects of such news.

Keywords: Statistical Physics; Omori Law; Bond Markets; Stock Markets; News; COVID-19

JEL codes: G15, G18, G41

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1 Introduction

The spread of the novel coronavirus (SARS-CoV-2) has posed unprecedented economic and financial turmoils in most of the countries, representing a massive geo-economic shock to the worldwide economy. Starting from China, the shock expanded to the international scene hitting financial markets all over the globe. During the period ranging from 20 February 2020 to 20 March 2020, the US S&P 500 lost as much as 31.7%, whereas the UK FTSE 100 dropped by 30.2%. The Euro area saw its financial markets severely plummeting as well, with the German DAX index declining by 49.3%, the Italian FTSE MIB losing 37.3%, and the Spanish IBEX 35 dropping of as much as 35.1%. Also government bond markets have been massively impacted as a consequence of the epidemic spread: the 1-Year US Treasury securities yield declined from 1.47 to 0.14 - a 90.5% drop - whereas the UK 1-Year bond yield saw its value decreasing from 0.635 to 0.083 - an almost 87% negative yield. Worldwide governments, along with central banks, have put in place unprecedented recovery plans to cope with the economic impact of the pandemic.

Several researchers have recently investigated the impact of official announcements regarding SARS-CoV-2 on global financial markets, highlighting the role of the pandemic as a source of financial volatility, and that of response policies as potential spreaders of further uncertainties into global financial markets (see, e.g., Zhang et al. 2020, Bakas and Triantafyllou 2020, Albulescu 2020, Caggiano et al. 2020 and Hanke et al. 2020). Although there is a general attention to equity market reactions, the impact and persistence analysis of equity and government bond market volatility shocks induced by SARS-CoV-2 related announcements is still an open question.

SARS-CoV-2 news can be regarded as earthquake mainshocks, whose associated foreshocks and aftershocks impact the volatility dynamics of financial markets. Pre-shock and aftershock rates and intensities can be described by several widely known empirical laws, such as the Omori law. According to the Omori law, aftershock rates decrease over time roughly by the reciprocal of time which follows the earthquake mainshock. In the context of financial markets, Sornette et al. (1996) studied the behaviour of the S&P 500 index before and after the Black Monday of 19 October 1987, finding that the implied market volatility after the market crash has follows a power-law with a log-periodic rate of decay. The studies of Lillo and Mantegna (2003, 2004) on the NYSE in the neighbourhood of the Black Monday crash find evidence on the fact that the rate of extreme volatility spikes follows a power-law that is equivalent to the modified Omori law. The applications of Selçuk and Gençay (2006), Weber et al. (2007) and Mu and Zhou (2008) on several stock market indices showed how the non-linearity of the return and volatility distributions of stock indices before and after a shock allows to employ the Omori law to describe the volatility outburst, as well as that the memory in volatility is induced not only by the main crashes, but also by sub-crashes.

Against this background, we investigate the impact of SARS-CoV-2 related news on major equity and bond markets through the lens of seismology (see Utsu 1961; Omori 1894), deriving parallels between energy dissipation and market volatility cascades. In the context of asset price perturbations (see e.g. Fama 1965; Ding et al. 1993; Mantegna and Stanley 1999; Danielsson et al. 2012), we employ the Omori law, which characterises the non-stationary phase observed in the neighbourhood of an earthquake, to study the foreshock and aftershock dynamics of financial systems agitated by the occurrence of extreme events related to the epidemics. Additionally, we study the relationship between the mainshocks and their largest aftershocks through Bath's law. Previous research on the relaxation dynamics of financial markets after crashes has shown that the power-law tail is adequate in describing their volatility patterns after major shocks (see, e.g., Lillo and Mantegna 2003, 2004; Selçuk 2004; Selçuk and Gençay 2006; Petersen et al. 2010a,b; Spelta et al. 2021).

Earthquakes are prominent examples of complex phenomena showing scale-invariance and fractality properties, prominent features which have been frequently observed in financial market data (see Liu et al. 2007; Barunik et al. 2012; Morales et al. 2013; Buonocore et al. 2016). The emergence of these properties is an indication of complexity and nonlinear dynamics in the context of the earthquake generation process. News effects can be conceived as earthquakes, which shock financial markets with a mainshock propagating across venues over time. Further, they can generate aftershocks, which indicate that the market is still discounting the news effects over time. This is in line with the extant literature investigating financial market crashes as earthquakes (see, for instance, Mart and Aminoto 2007; Mu and Zhou 2008; Jiang et al. 2009; Siokis 2012; Jiang et al. 2013; Negrea 2014; Xu et al. 2014; Jagielski et al. 2017; Da Cunha and da Silva 2020).

We study the country-specific effects of socio-economic and political news, including financial stimulus announcements, on a group of representative countries, whose financial systems have been significantly impacted by the evolution of the epidemics, over the period from January 2020 to April 2020. In other words, we investigate cascade effects on the volatility patterns of the reference equity market of the US (S&P500), the UK (FTSE100), Spain (IBEX35), France (CAC40), Germany (DAX) and Italy (FTSE-MIB) and of each country's 1-Year bond yield. This allows us to determine which markets are more efficient at incorporating SARS-CoV-2 related news and to characterise which is their foreshock and aftershock dynamics towards such exogenous shocks.

Our approach can be extended and integrated in a multivariate setting with the statistical and econometric framework on interconnectedness, systemic risk and spillover measurement. The information shares developed by Hasbrouck (1995) and the common factor components of Gonzalo and Granger (1995) have been widely employed in the empirical literature - see, for instance, Mizrach and Neely (2008), Pagnottoni and Dimpfl (2019), Grammig and Peter (2013). Additionally, the systemic risk and spillover framework proposed by Diebold and Yilmaz (2012); Diebold and Yılmaz (2014) has given rise to a variety of financial applications - e.g. Demirer et al. (2018), Giudici and Pagnottoni (2020), Giudici and Pagnottoni (2019) and Giudici et al. (2021). Possible extensions of the work might also involve alternative econometric measures of connectedness as in Billio et al. (2012), systemic risk measures as in Abedifar et al. (2017), and news contagion risk as in Cerchiello et al. (2017). Such approaches could unveil relevant information on the interaction of different markets when common shocks occur.

The paper proceeds as follows. Section 2 introduces the Omori law and its linkage with the financial volatility dynamics. Section 3 presents and discusses the results. Section 4 concludes.

2 Methodology

Let us denote the time of announcement of a generic SARS-CoV-2 related event as T_s. We aim at studying the decay of massive volatility fluctuations in the k days before and after the announcement date T_s, which we set at $k = 10$ days in the present context. Denoting the price of the generic asset (equity or bond yield) i at time t as $P_i(t)$, we determine the daily market volatility of as:

$$V_i(t) = |\log(P_i(t)) - \log(P_i(t-1))|. \tag{1}$$

We consider the 10-base logarithm scale as frequently done in seismology. This is because the number of aftershocks which follow an earthquake mainshock has been shown to be linearly dependent on displacement time when represented in its 10-base logarithm scale (see Omori 1894).

From Eq. 1, denoting as q_i the value of the q-th percentile[1] of the volatility distribution of the time series i, we derive the correspondent binary volatility time series $n_i(t)$ as:

$$n_i(t) = \begin{cases} 1, & V_i(t) \geq q_i \\ 0, & V_i(t) < q_i. \end{cases}$$

In other words, in this way we investigate the number of times a volatility time series assumes larger values than the considered threshold. This is equivalent to study the number of aftershocks measured at time t after the earthquake's mainshock. The choice of selecting a threshold to compute the binary volatility series is in accordance with previous related research (see Weber et al. 2007; Petersen et al. 2010a,b; Nowak et al. 2011). Furthermore, Lillo and Mantegna (2003, 2004) show that, in the aftermath of a market crash, the volatility can be represented as a stochastic process with a power-law decay rate, which makes pure

[1]We consider the 85-th percentile of the volatility distribution as a threshold to classify the volatility series outburst and the volatility regimes in regular background activity.

autoregressive models, such as GARCH models, less adequate in describing the observed aftershock volatility dynamics.

We then study the response of financial and bond markets to SARS-CoV-2 related news through tools developed in the field of seismology. Specifically, we provide parallels between the energy relaxation process occurring after main shocks in the context of earthquakes and the market volatility cascades generated by SARS-CoV-2 related announcements. The Omori law (Omori 1894) provides a theoretical framework for quantifying the magnitude of pre- and after-shock volatility decays in time (see, for instance, Petersen et al. 2010a,b; Zawadowski et al. 2006; Ponzi et al. 2009), as well as it detects statistical regularities in geophysical earthquakes (see Utsu 1961). Indeed, as per the Omori law, the number of after-shock earthquakes per unit time, measured at time t, decays following a power law. In other words, the rate of high volatility counts $N(t)$ following a single perturbation at time T_s is given by:

$$N_i(|t - T_s|) \sim |t - T_s|^{-\beta_{N_i}} \tag{2}$$

where β_{N_i} is the parameter representing the Omori power law exponent, and $N_i(t) = \frac{1}{J}\sum_{j=1}^{J} n_{i,j}(t)$ is the average rate of high volatility occurrences induced by the set of J events in the generic asset i. With the aim of estimating the power law relationship between high volatility regimes and displacement time $\tau = |t - T_s|$, we derive the cumulative number of events above the threshold q at time t as:

$$\Phi_i(|t - T_s|) = \int_{T_s}^{t} N_i(|t' - T_s|)dt' \propto |t - T_s|^{1-\beta_{N_i}} \tag{3}$$

Then, we compare the volatility dynamics preceding and following SARS-CoV-2 related events by discerning between $N_i^{Pre}(t|t < T_s)$ and $N_i^{Aft}(t|t > T_s)$. Finally, by performing an ordinary least square estimation on a log-log scale we derive the pre- and after-shock Omori power-law exponents, denoted as $\beta_{N_i}^{Pre}$ and $\beta_{N_i}^{Aft}$, respectively.

The Omori exponents are useful to quantify volatility reactions to SARS-CoV-2 related news. The higher the Omori exponents, the faster the reaction of the market to SARS-CoVannouncements - during the foreshock phase - and absorption of the shock - during the aftershock phase - are. Conversely, the lower the exponents, the slower the shock is perceived by the market - during the foreshock phase - and the more relaxed the market comes back to its equilibrium state after the shock has occurred - during the aftershock phase.

We illustrate the previously discussed concept in Figure 1, which gives an overview of the interpretation of the Omori exponents. To this aim, we simulate 1000 power law realizations with two representative β parameters, equal to 0.2 and 0.1, for 20 points in time (comprising the foreshock and aftershock period). We average across the simulated distributions and obtain the volatility distributions illustrated in the main panel of Figure 1. Notice how the simulated volatility distribution with β equal to 0.2 is more peaked towards the event date than that having a β of 0.1, with a faster relaxation dynamics both during the pre-shock and after-shock periods. We then represent the cumulative distribution function from $t_0 = 0$ backwards (foreshock) and that from t_0 onwards (after shock) for the two power law distributions. The different "V" shapes and, in particular, the inclinations of the cumulative distribution functions indicate that a higher power law exponent corresponds to a faster volatility decay.

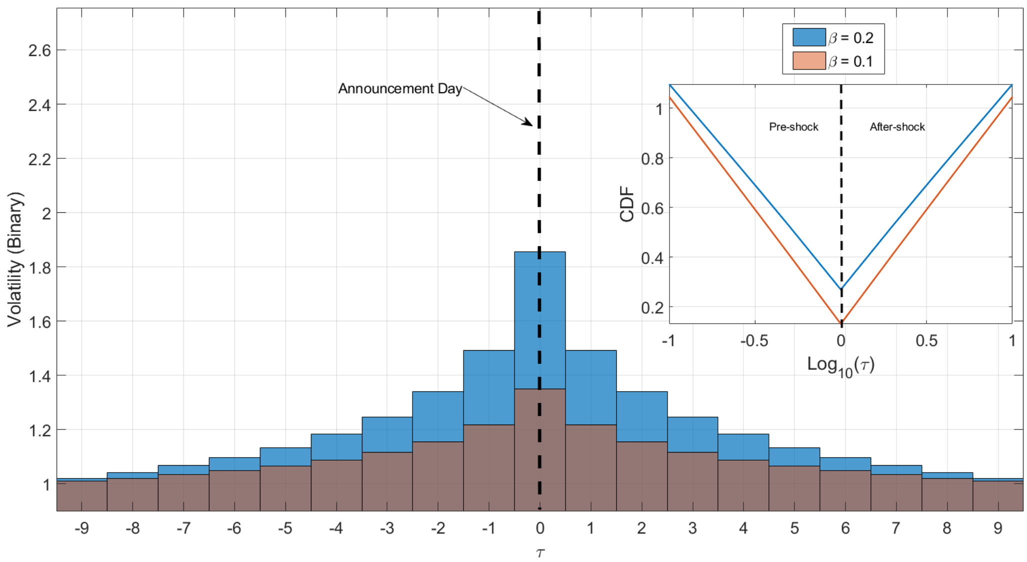


Figure 1: **Simulated volatility patterns and Omori exponents.** The main panel shows the simulated volatility patterns for two different power laws with β equal to 0.2 (in blue) and 0.1 (in red). The inset illustrates the dynamics of the cumulative distribution function from $t_0 = 0$ backwards (foreshock) and that from t_0 onwards (after shock) for the two power law distributions.

In addition, it is worth investigating the relationship between the size of the largest shock $V_1 = V(T_c)$ and that of the second one V_2, both before and after T_c. For this purpose, the Bath law parameter, which we denote as B, expresses the relation between V_1 and V_2, i.e.

$$M_1 - M_2 = log_{10}(V_1) - log_{10}(V_2) = B \tag{4}$$

The aforementioned functional form implies the following relationship between the two volatility shocks:

$$V_2/V_1 = C_B \tag{5}$$

and, thus, $B = -log_{10} C_B$.

3 Empirical results

As a preliminary analysis, we compare the volatility patterns of each country equity index and bond yield series in the neighbourhood of SARS-CoV-2 related news. A comprehensive list of the considered country-specific events can be found in Tables 1-6. We select major events related to the evolution of the epidemics between January 2020, when the first cases manifested, and the end of April 2020, thus including the majority of the first wave of lockdown and mobility restriction measures, the announcements of economic aid packages (both from single countries and supranational authorities), and the lockdown lifting decisions.

United States	
20/01/2020	First confirmed case.
29/02/2020	First reported death.
11/03/2020	The World Health Organization's Director-General declares that COVID-19 can be characterized as a pandemic.
13/03/2020	Approval of an aid economic package for workers and individuals.
16/03/2020	Trump issues guidelines to avoid social gatherings and to restrict discretionary travels.
22/03/2020	Trump announces the approval of Washington emergency declaration.
24/03/2020	The White House and Senate leaders of both parties announced agreement of a $2 trillion measure to aid workers, businesses and the healthcare system.
06/04/2020	The Federal Reserve announces it will support banks that lend to small businesses.
14/04/2020	The International Monetary Fund estimates global GPD to decline of about 3%.
15/04/2020	Trump announces guidelines on reopening the US economy.

Table 1: **United States SARS-CoV-2 related events.** The table shows major SARS-CoV-2 related events in the United States during the period 20 January 2020 - 30 April 2020.

Figure 2 shows that the largest part of the SARS-CoV-2 related events is concentrated

Germany	
25/02/2020	First confirmed cases in the Baden-Württemberg region.
09/03/2020	First reported death.
10/03/2020	Merkel announces up to 70% of Germany could become infected.
11/03/2020	Merkel announces liquidity support for companies.
	The World Health Organization's Director-General declares that COVID-19 can be characterized as a pandemic.
17/03/2020	The health threat switches from moderate to high.
23/03/2020	The government decides on a financial aid package of €750 billion.
24/03/2020	The European Commission approves, under the Temporary Framework, a German scheme to support companies.
	G7 finance ministers and central bank governors meeting, pledging to do "whatever is necessary" to help their economies recover from the coronavirus.
01/04/2020	Social distancing measures are extended until April 19th.
09/04/2020	The ministers of Finances of the Eurozone countries agreed to a €500 billions aid, including the possibility of using the European Stability Mechanism.
14/04/2020	The International Monetary Fund estimates global GPD to decline of about 3%.
23/04/2020	The European Council approves a financial aid package worth €540 billions.
30/04/2020	The European Central Bank announces new pandemic emergency longer-term refinancing operations.

Table 2: **Germany SARS-CoV-2 related events.** The table shows major SARS-CoV-2 related events in Germany during the period 20 January 2020 - 30 April 2020.

France	
24/01/2020	First confirmed case.
14/02/2020	First reported death.
10/03/2020	Introduction of mobility and activities restrictions.
11/03/2020	The World Health Organization's Director-General declares that COVID-19 can be characterized as a pandemic.
16/03/2020	Announcement of national lockdown.
17/03/2020	The French Finance Minister Le Maire announces a €45 billions aid package for small businesses and other hard-hit sectors.
24/03/2020	The European Commission approves, under Article 107(3)(b), three French State aid schemes.
	G7 finance ministers and central bank governors meeting, pledging to do "whatever is necessary" to help their economies recover from the coronavirus.
14/04/2020	The International Monetary Fund estimates global GPD to decline of about 3%.
23/04/2020	The European Council approves a financial aid package worth €540 billions.
28/04/2020	The Prime Minister reveals plans to ease SARS-CoV-2 lockdown measures.
30/04/2020	The European Central Bank announces new pandemic emergency longer-term refinancing operations.

Table 3: **France SARS-CoV-2 related events.** The table shows major SARS-CoV-2 related events in the France during the period 20 January 2020 - 30 April 2020.

Spain	
31/01/2020	First confirmed case.
12/02/2020	First reported death.
09/03/2020	State of emergency declaration in the community of Madrid.
10/03/2020	The European Commission proposes to "free up €7.5 billions of liquidity".
11/03/2020	The World Health Organization's Director-General declares that COVID-19 can be characterized as a pandemic.
13/03/2020	The state of emergency is extended to the whole country.
15/03/2020	Declaration of national lockdown.
17/03/2020	Announcement of a €200 billions support package.
22/03/2020	Lockdown measures are extended until April 11th.
24/03/2020	G7 finance ministers and central bank governors meeting, pledging to do "whatever is necessary" to help their economies recover from the coronavirus.
09/04/2020	The ministers of Finances of the Eurozone countries agree to a €500 billions aid, including the possibility of using the European Stability Mechanism.
13/04/2020	Adoption of some gradual measures for easing the lockdown.
14/04/2020	The International Monetary Fund estimates global GPD to decline of about 3%.
23/04/2020	The European Council approves a financial aid package worth €540 billions.
28/04/2020	Unveiling of a gradual exit strategy from lockdown
30/04/2020	The European Central Bank announces new pandemic emergency longer-term refinancing operations.

Table 4: **Spain SARS-CoV-2 related events.** The table shows major SARS-CoV-2 related events in Spain during the period 20 January 2020 - 30 April 2020.

Italy	
31/01/2020	First confirmed cases in Rome (Chinese couple).
20/02/2020	First confirmed case in Codogno.
22/02/2020	First death in Veneto and creation of the first "red zones" in Lombardy and Veneto.
09/03/2020	Declaration of national lockdown.
10/03/2020	The European Commission proposes to "free up €7.5 billions of liquidity".
11/03/2020	Further restrictions on lockdown related to travel and approval of a €25 billions financial package. The World Health Organization's Director-General declares that COVID-19 can be characterized as a pandemic.
21/03/2020	Halt to all non-essential production activities.
24/03/2020	G7 finance ministers and central bank governors meeting, pledging to do "whatever is necessary" to help their economies recover from the coronavirus.
06/04/2020	Announcement of an economic stymulus worth €200 billions.
09/04/2020	The ministers of Finances of the Eurozone countries agreed to €500 billion aid, including the possibility of using the ESM
14/04/2020	The International Monetary Fund estimates global GPD to decline of about 3%.
23/04/2020	The European Council approves a financial aid package worth €540 billions.
24/04/2020	Conversion of the "Cura Italia" decree into law.
26/04/2020	New prime minister decree on the beginning of the "phase 2" for the reopening of economic activities and the easing of mobility restrictions.
30/04/2020	The European Central Bank announces new pandemic emergency longer-term refinancing operations.

Table 5: **Italy SARS-CoV-2 related events.** The table shows major SARS-CoV-2 related events in the Italy during the period 20 January 2020 - 30 April 2020.

United Kingdom	
31/01/2020	First confirmed cases.
11/03/2020	The World Health Organization's Director-General declares that COVID-19 can be characterized as a pandemic.
12/03/2020	The Chief Medical Officers raises the risk for the UK from moderate to high.
16/03/2020	Prime Minister Johnson advises everyone against non-essential travel and contact with others.
17/03/2020	Chancellor Sunak announces that £330 billions would be made available in loan guarantees for businesses affected by the pandemic.
19/03/2020	The government introduces the Coronavirus Bill 2019–21.
23/03/2020	Prime Minister Johnson announces that measures to mitigate the virus will to be tightened further.
24/03/2020	G7 finance ministers and central bank governors meeting, pledging to do "whatever is necessary" to help their economies recover from the coronavirus.
28/03/2020	Fitch downgrades the UK to AA-.
14/04/2020	The Office for Budget Responsibility publishes a scenario under which UK GDP would fall by 35% in the second quarter of 2020. The International Monetary Fund estimates global GPD to decline of about 3%.

Table 6: **United Kingdom SARS-CoV-2 related events.** The table shows major SARS-CoV-2 related events in the United Kingdom during the period 20 January 2020 - 30 April 2020.

around the middle of March, when lockdown and intervention policies were globally put in place, and in April, when governments' reaction plans have been announced and major economic outlooks released. Notice that equity and bond markets have a different reaction to SARS-CoV-2 news. Volatility series of equity indices peak on March 11th, when the World Health Organization recognized SARS-CoV-2 as a pandemic (see WHO 2020), while bond yields present a greater reaction during macroeconomic announcements, such as on 23 March when the European Commission announced a financial aid package of 750 bln Euros to mitigate the negative economic consequences of SARS-CoV-2 outbreak, and on 14 April when the IMF negative World Economic Outlook was released (see IMF 2020).

From Figure 3 we notice that the volatility dynamics of equity markets are highly cor-

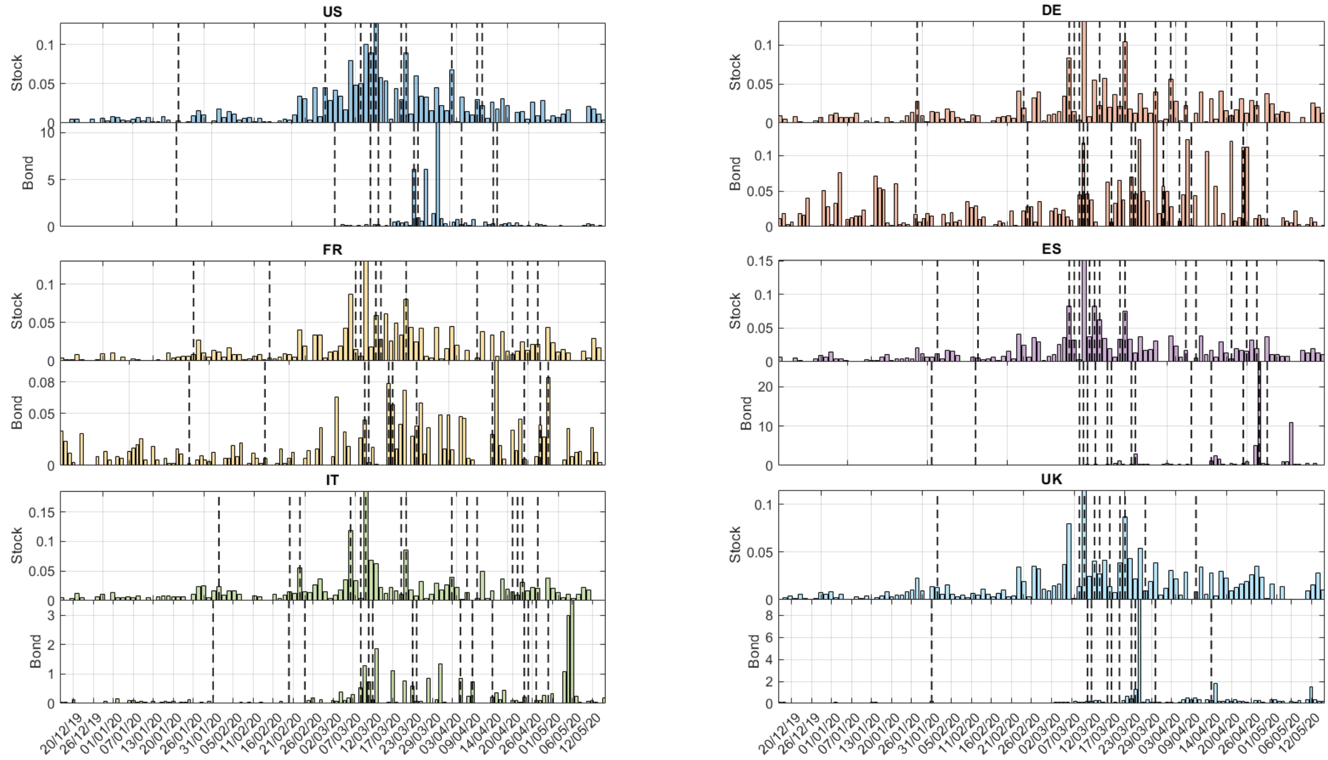
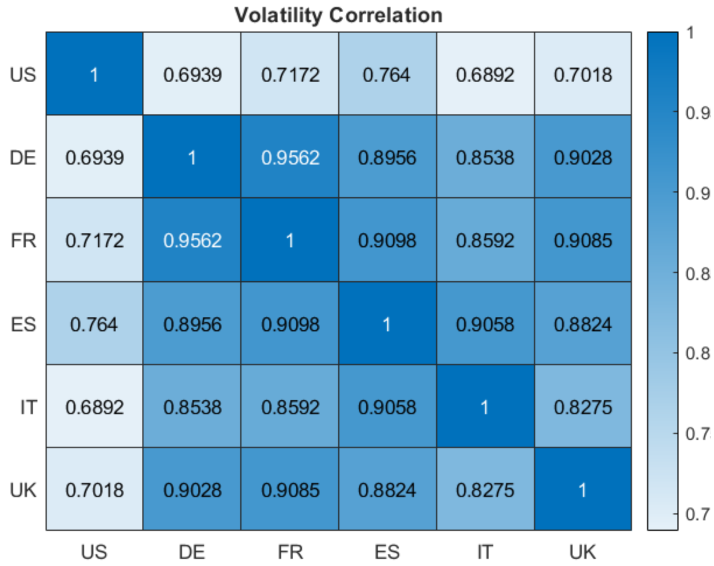


Figure 2: **Volatility patterns for selected equity indices and bond yields along with the events dates.** Column bars represent, for each country, the daily volatility of the reference index (upper panel) and the daily volatility of the reference bond yields (lower panel). The dashed black lines identify the dates of the relevant events, which mainly impacted the course of the national equity and bond markets.

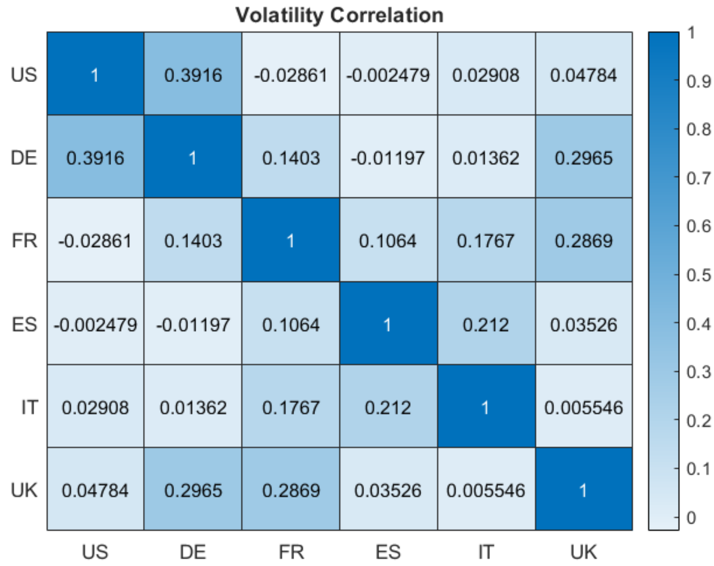
related, with a lower bound of 0.689, which represents the Pearson correlation coefficient between the S&P500 and the FTSE-MIB, and an upper bound of 0.9562 between CAC40 and DAX, whereas bond yields volatility correlations are less pronounced during the same period, exhibiting even negative values.

In Figure 4 we show the volatility distributions of equity indices and bond yields along with their 85-th percentiles taken as a benchmark for large volatility deviations. The figure confirms that, overall, we do isolate normal background activity of financial volatilities with the choice of our percentile, therefore ensuring we are taking into account only for extreme values of the financial time series.

Figure 5 illustrates how SARS-CoV-2 related news impacted the volatility fluctuations of equity and bond markets both during the pre-shock and after-shock phases. In particular, the upper panels show the average empirical cumulative distribution function (CDF) of abnormal volatility movements preceding and following major SARS-CoV-2 news for the selected equity

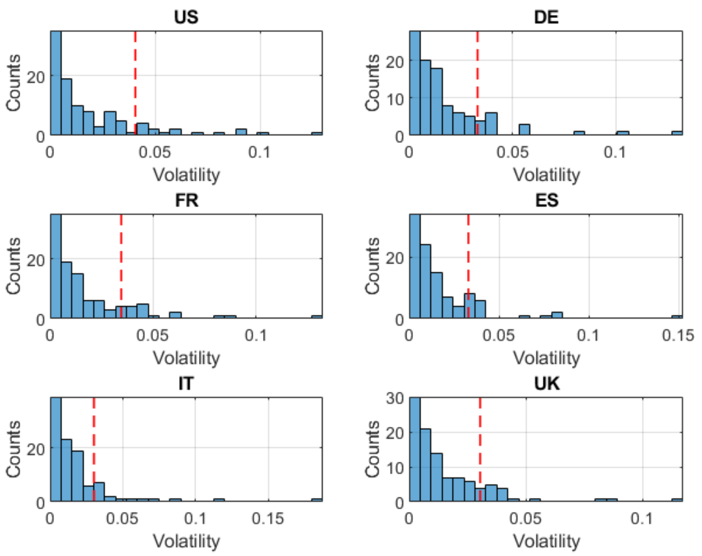


(a) Equity

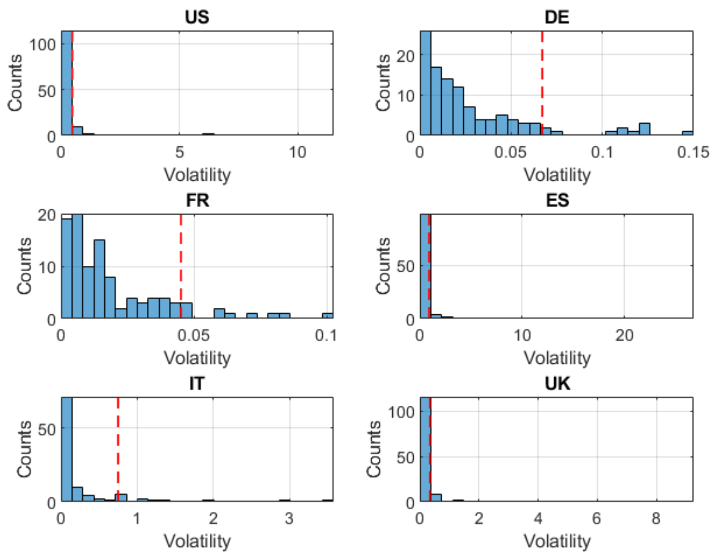


(b) Bond

Figure 3: **Volatility correlations across equity indices and bond yields.** The figure shows the pairwise Pearson correlation coefficients among the volatility series of the considered financial indices (left panel) and bond yields (right panel). Darker colors correspond to higher correlated pairs.



(a) Equity

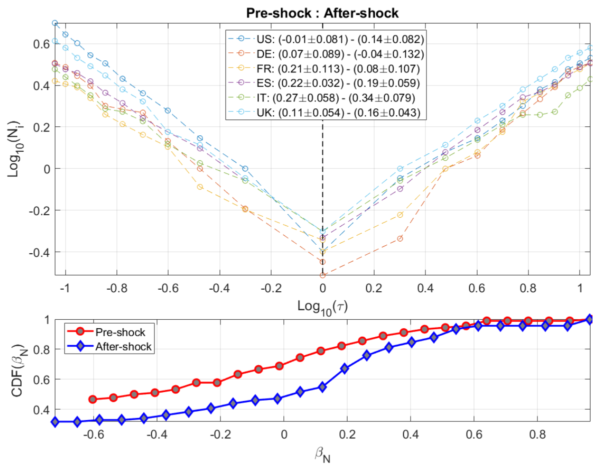


(b) Bond

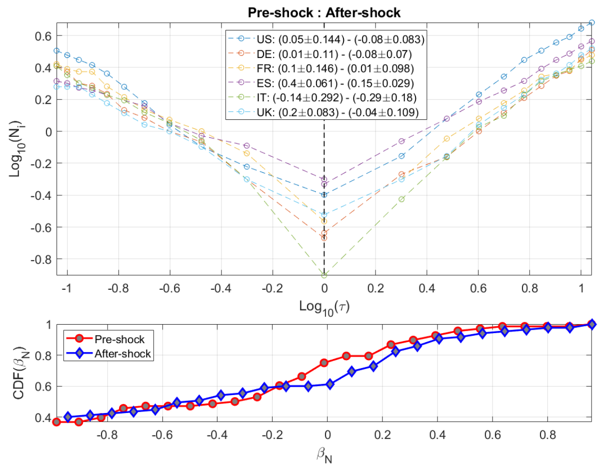
Figure 4: **Volatility distributions of equity indices and bond yields.** The figure reports the volatility distributions for the reference financial indices (left panels) and bond yields (right panels). Red dashed lines the 85-th percentiles taken as reference for identifying high volatility movements.

indices (left panel) and 1-Year bond yields (right panel). The corresponding Omori power-law exponents, along with their confidence interval, are reported in the legend.

The Omori exponents are instrumental to evaluate how markets react to SARS-CoV-2



(a) Equity



(b) Bond

Figure 5: **Average distribution of large volatility occurrences and Omori exponents.** The upper panels report the log-log plot of the average cumulative distribution of large volatility movements around the days of SARS-CoV-2 related announcements. The legend provides the values of the Omori exponents for both pre-shocks and after-shocks. The lower panels show the cumulative distributions of the pooled pre-shock and after-shock Omori exponents. In particular, the red color is used to identify the empirical CDF of the pre-shock exponents, while the blue color is associated with the after-shock distribution. Results are presented both for the selected equity indices (left panel) and bond yields (right panel).

related announcements. Results show heterogeneity in the values of the Omori exponents. In the equity market, Italian and Spanish indices exhibit large exponent values, if compared to the other countries in the sample. In other words, SARS-CoV-2 related news induced sudden volatility jumps in these markets, rapidly absorbed in the after-shock time-span. This dynamics is arguably due to the fact that these countries were among the first ones affected by the spread of the disease, which fostered the sensitivity of their respective financial indices. The Omori exponents related to the CAC index, instead, suggest that SARS-CoV-2 news produce high volatility jump on the French financial market, which are slowly re-absorbed during the post-shock phase. Evidences also suggest that volatility outbursts related to the UK equity index are built up more slowly than the other markets before the shock, whereas the US equity index exhibits a slower volatility relaxation dynamics than other countries firstly affected by the virus.

The bond yield series show Omori exponents that are more heterogeneously distributed across countries. Indeed, we observe that the pre-shock exponents are relatively high in Spain and, partially, in France if compared with the after-shock exponents, meaning that bond markets seem to exhibit sudden volatility jumps just prior the occurrence of news, which are then slowly reabsorbed by market dynamics. In other cases, a similar behaviour emerges only for the pre-shock phase, such as for the UK bond index. Interestingly, we also find negative aftershock exponents, although statistically significant only for Italy and Germany in the aftershock, which can be interpreted as a dominance of aftershocks further away from mainshocks over the volatility cascade around the main event date. More in general, bond yields show lower Omori exponents than those observed for equity indices, thus suggesting that the bond market incorporate less efficiently SARS-CoV-2 related shocks.

In the lower panels of Figure 5 we illustrate the empirical CDF of the two Omori exponents - β^{Aft} and β^{Pre} - computed by pooling the entire set of SARS-CoV-2 news. The after-shock empirical CDF of β_N for the equity indices shows larger values if compared to the pre-shock distribution. Thus, higher values of β^{Aft} with respect to β^{Pre} indicate that the response time after the news date T_s is generally shorter than the activation time leading to it. When considering bond yields, instead, the difference between β^{Aft}, and β^{Pre} is less prominent. This suggests that volatility in the bond markets induced by SARS-CoV-2 announcements is more persistent than that of equity markets, which instead reacts more timely to such exogenous shocks. This empirical outcome is in line with the studies on cross-market financial shock transmission, which find that the volatility shocks in the equity market are absorbed much more quickly than those in the bond one - see, for instance, Tian and Hamori (2016).

Finally, we study the relationship between the size of the largest shock $V_1 = V(T_c)$ and the second largest shock V_2, before and after T_c by means of the Bath law. Figure 6 reports a scatter plot of V_1 and $V_{2,aft}$, where aft stands for aftershock, for the equity market, which shows a linear relation corresponding to $B_{Aft} = 0.023$ while for the pre-shock case (indicated by pre) we have $B_{Pre} = 0.16$. Similarly, for the bond market (see Figure 7) we find about $B_{Aft} = 0.199$ for the after-shock case and for the pre-shock case we report $B_{Pre} = 0.089$.

On the one hand, comparing the values of B_{Pre} and B_{Aft}, evidence supports the fact that the magnitude of pre-shocks preceding a volatility mainshock in the stock markets is generally larger than that of the aftershocks which immediately follow it. On the other hand, the size

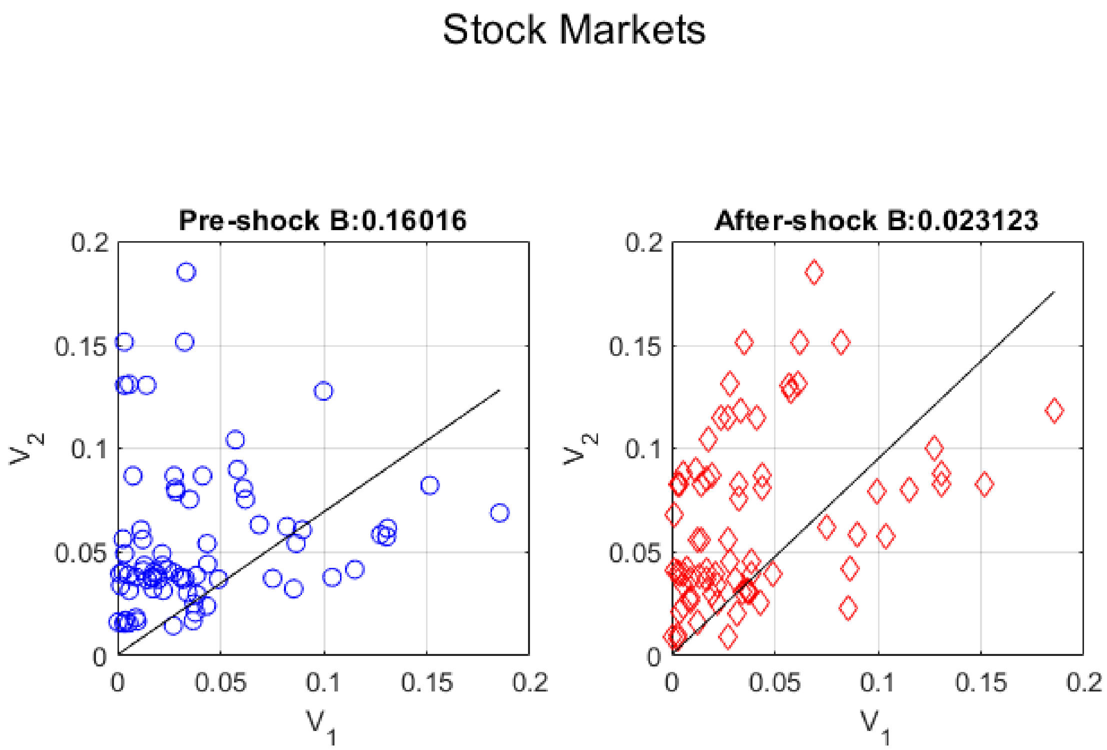


Figure 6: **The relationship between the size of the main shock $V(T_c)$ and the size of the second largest aftershock (or pre-shock) V_2 for the stock market.** As with the Bath law for earthquakes, we observe a proportional relation $V_2 = C_B V(T_c)$ which corresponds to a Bath parameter $B = -log_{10}C_B$. For the after-shock case we have $B_{Aft} = 0.023$ and for the pre-shock case we report $B_{Pre} = 0.16$.

of volatility aftershocks which follow a mainshock is generally greater than that related to pre-shocks in the bond market. This provides further evidence on the fact that the effects of SARS-CoV-2 news shocks are more persistent in the credit market rather than in the stock market.

4 Concluding remarks

The spread of the novel SARS-CoV-2 has posed unprecedented economic and financial challenges for all the world countries, bearing a striking geo-economic shock to their financial markets. Economists such as Baker et al. (2020) and Bram et al. (2020) relate the current pandemic outbreak to a natural disaster rather than to an economic recession. Indeed, such

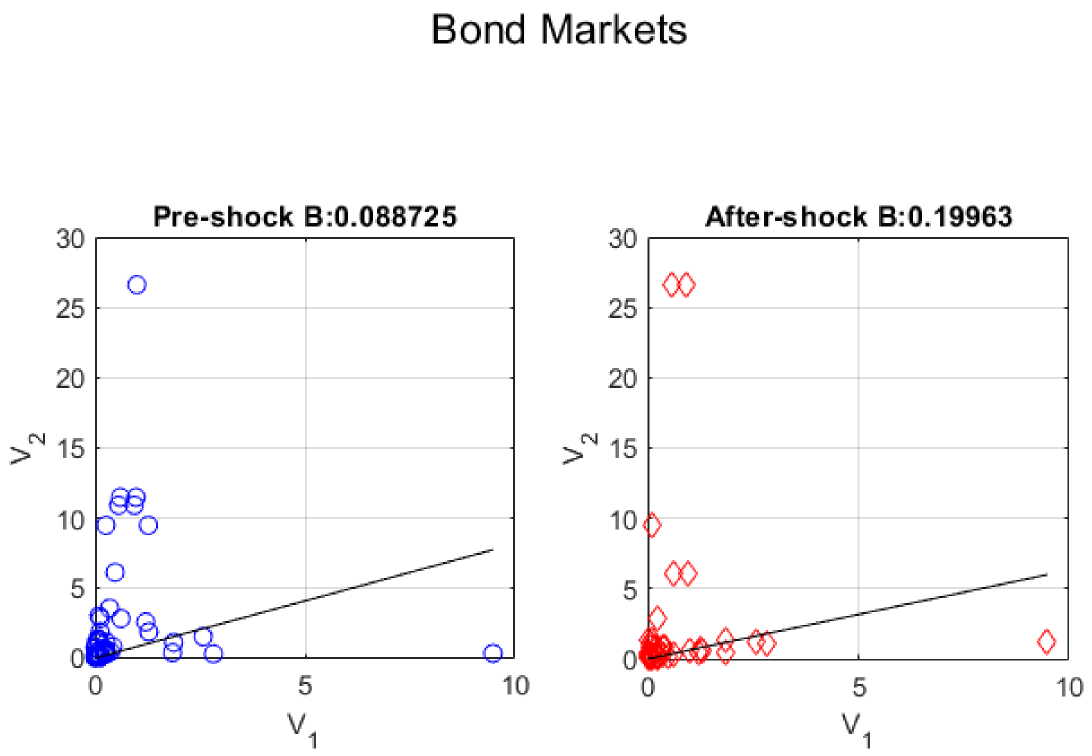


Figure 7: **The relationship between the size of the main shock $V(T_c)$ and the size of the second largest aftershock (or pre-shock) V_2 for the bond market.** As with the Bath law for earthquakes, we observe a proportional relation $V_2 = C_B V(T_c)$ which corresponds to a Bath parameter $B = -log_{10} C_B$. For the after-shock case we have $B_{Pre} = 0.088$ and for the pre-shock case we report $B_{Aft} = 0.199$.

an exogenous event has hit the markets in the same way as an earthquake, inducing foreshock and aftershock volatility spikes in financial markets worldwide around the neighbourhood of SARS-CoV-2 major events. In line with cascade effects of energy propagation which occur after earthquakes, we have proposed to investigate whether SARS-CoV-2 related news produce dynamic relaxation in the financial volatility of major equity indices and government bond yields.

Our empirical investigation provides evidence on the fact that: (i) financial markets heterogeneously react to news related to the pandemics, depending on their reference country, and on their foreshock and aftershock behaviour; (ii) financial markets firstly impacted by the epidemics tend to discount news effects earlier, although the impact of shocks on the Italian and German bond markets are deferred with respect to the actual date of announcement; (iii) bond market foreshocks and aftershocks are almost symmetric in their dynamics, whereas for equity markets the aftershock relaxation dynamics is faster than the foreshock volatility outburst; (iv) the sovereign bond market is generally less efficient than the equity market at incorporating volatility shocks, meaning that volatility shocks induced by SARS-CoV-2 related events are more persistent in the credit market.

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References

Abedifar, P., Giudici, P., and Hashem, S. Q. (2017). Heterogeneous market structure and systemic risk: Evidence from dual banking systems. *Journal of Financial Stability*, 33:96–119.

Albulescu, C. T. (2020). Covid-19 and the united states financial markets' volatility. *Finance Research Letters*, page 101699.

Bakas, D. and Triantafyllou, A. (2020). Commodity price volatility and the economic uncertainty of pandemics. *Economics Letters*, 193:109283.

Baker, S. R., Bloom, N., Davis, S. J., and Terry, S. J. (2020). Covid-induced economic uncertainty. Technical report, National Bureau of Economic Research.

Barunik, J., Aste, T., Di Matteo, T., and Liu, R. (2012). Understanding the source of multifractality in financial markets. *Physica A: Statistical Mechanics and its Applications*, 391(17):4234–4251.

Billio, M., Getmansky, M., Lo, A. W., and Pelizzon, L. (2012). Econometric measures of connectedness and systemic risk in the finance and insurance sectors. *Journal of financial economics*, 104(3):535–559.

Bram, J., Deitz, R., et al. (2020). The coronavirus shock looks more like a natural disaster than a cyclical downturn. Technical report, Federal Reserve Bank of New York.

Buonocore, R. J., Aste, T., and Di Matteo, T. (2016). Measuring multiscaling in financial time-series. *Chaos, Solitons & Fractals*, 88:38–47.

Caggiano, G., Castelnuovo, E., and Kima, R. (2020). The global effects of covid-19-induced uncertainty. *Economics Letters*, 194:109392.

Cerchiello, P., Giudici, P., and Nicola, G. (2017). Twitter data models for bank risk contagion. *Neurocomputing*, 264:50–56.

Da Cunha, C. and da Silva, R. (2020). Relevant stylized facts about bitcoin: Fluctuations, first return probability, and natural phenomena. *Physica A: Statistical Mechanics and its Applications*, 550:124155.

Danielsson, J., Shin, H. S., and Zigrand, J.-P. (2012). Endogenous extreme events and the dual role of prices. *Annu. Rev. Econ.*, 4(1):111–129.

Demirer, M., Diebold, F. X., Liu, L., and Yilmaz, K. (2018). Estimating global bank network connectedness. *Journal of Applied Econometrics*, 33(1):1–15.

Diebold, F. X. and Yilmaz, K. (2012). Better to give than to receive: Predictive directional measurement of volatility spillovers. *International Journal of Forecasting*, 28(1):57–66.

Diebold, F. X. and Yılmaz, K. (2014). On the network topology of variance decompositions: Measuring the connectedness of financial firms. *Journal of Econometrics*, 182(1):119–134.

Ding, Z., Granger, C. W., and Engle, R. F. (1993). A long memory property of stock market returns and a new model. *Journal of empirical finance*, 1(1):83–106.

Fama, E. F. (1965). The behavior of stock-market prices. *The journal of Business*, 38(1):34–105.

Giudici, P., Leach, T., and Pagnottoni, P. (2021). Libra or librae? basket based stablecoins to mitigate foreign exchange volatility spillovers. *Finance Research Letters*, page 102054.

Giudici, P. and Pagnottoni, P. (2019). High frequency price change spillovers in bitcoin markets. *Risks*, 7(4):111.

Giudici, P. and Pagnottoni, P. (2020). Vector error correction models to measure connectedness of bitcoin exchange markets. *Applied Stochastic Models in Business and Industry*, 36(1):95–109.

Gonzalo, J. and Granger, C. (1995). Estimation of common long-memory components in cointegrated systems. *Journal of Business & Economic Statistics*, 13(1):27–35.

Grammig, J. and Peter, F. J. (2013). Telltale tails: A new approach to estimating unique market information shares. *Journal of Financial and Quantitative Analysis*, pages 459–488.

Hanke, M., Kosolapova, M., and Weissensteiner, A. (2020). Covid-19 and market expectations: Evidence from option-implied densities. *Economics Letters*, 195:109441.

Hasbrouck, J. (1995). One security, many markets: Determining the contributions to price discovery. *The journal of Finance*, 50(4):1175–1199.

IMF (2020). World economic outlook, april 2020: The great lockdown. Technical report, International Monetary Fund.

Jagielski, M., Kutner, R., and Sornette, D. (2017). Theory of earthquakes interevent times applied to financial markets. *Physica A: Statistical Mechanics and its Applications*, 483:68–73.

Jiang, J., Li, W., Cai, X., and Wang, Q. A. (2009). Empirical study of recent chinese stock market. *Physica A: Statistical Mechanics and its Applications*, 388(9):1893–1907.

Jiang, X., Chen, T., and Zheng, B. (2013). Time-reversal asymmetry in financial systems. *Physica A: Statistical Mechanics and its Applications*, 392(21):5369–5375.

Lillo, F. and Mantegna, R. N. (2003). Power-law relaxation in a complex system: Omori law after a financial market crash. *Physical Review E*, 68(1):016119.

Lillo, F. and Mantegna, R. N. (2004). Dynamics of a financial market index after a crash. *Physica A: Statistical Mechanics and its Applications*, 338(1-2):125–134.

Liu, R., Di Matteo, T., and Lux, T. (2007). True and apparent scaling: The proximity of the markov-switching multifractal model to long-range dependence. *Physica A: Statistical Mechanics and its Applications*, 383(1):35–42.

Mantegna, R. N. and Stanley, H. E. (1999). *Introduction to econophysics: correlations and complexity in finance*. Cambridge university press.

Mart, T. and Aminoto, T. (2007). Impact of the monetary crisis on statistical properties of the jakarta and kuala lumpur stock exchange indices. *Physica A: Statistical Mechanics and its Applications*, 373:634–650.

Mizrach, B. and Neely, C. J. (2008). Information shares in the us treasury market. *Journal of Banking & Finance*, 32(7):1221–1233.

Morales, R., Di Matteo, T., and Aste, T. (2013). Non-stationary multifractality in stock returns. *Physica A: Statistical Mechanics and its Applications*, 392(24):6470–6483.

Mu, G.-H. and Zhou, W.-X. (2008). Relaxation dynamics of aftershocks after large volatility shocks in the ssec index. *Physica A: Statistical Mechanics and its Applications*, 387(21):5211–5218.

Negrea, B. (2014). A statistical measure of financial crises magnitude. *Physica A: Statistical Mechanics and its Applications*, 397:54–75.

Nowak, S., Andritzky, J., Jobst, A., and Tamirisa, N. (2011). Macroeconomic fundamentals, price discovery, and volatility dynamics in emerging bond markets. *Journal of Banking & Finance*, 35(10):2584–2597.

Omori, F. (1894). On the aftershocks of earthquakes. *Journal of the College of Science*, 7:111–200.

Pagnottoni, P. and Dimpfl, T. (2019). Price discovery on bitcoin markets. *Digital Finance*, 1(1):139–161.

Petersen, A. M., Wang, F., Havlin, S., and Stanley, H. E. (2010a). Market dynamics immediately before and after financial shocks: Quantifying the omori, productivity, and bath laws. *Physical Review E*, 82(3):036114.

Petersen, A. M., Wang, F., Havlin, S., and Stanley, H. E. (2010b). Quantitative law describing market dynamics before and after interest-rate change. *Physical Review E*, 81(6):066121.

Ponzi, A., Lillo, F., and Mantegna, R. N. (2009). Market reaction to a bid-ask spread change: A power-law relaxation dynamics. *Physical Review E*, 80(1):016112.

Selçuk, F. (2004). Financial earthquakes, aftershocks and scaling in emerging stock markets. *Physica A: Statistical Mechanics and its Applications*, 333:306–316.

Selçuk, F. and Gençay, R. (2006). Intraday dynamics of stock market returns and volatility. *Physica A: Statistical Mechanics and its Applications*, 367:375–387.

Siokis, F. M. (2012). Stock market dynamics: Before and after stock market crashes. *Physica A: Statistical Mechanics and its Applications*, 391(4):1315–1322.

Sornette, D., Johansen, A., and Bouchaud, J.-P. (1996). Stock market crashes, precursors and replicas. *Journal de Physique I*, 6(1):167–175.

Spelta, A., Pecora, N., Flori, A., and Giudici, P. (2021). The impact of the sars-cov-2 pandemic on financial markets: a seismologic approach. *Annals of Operations Research*, pages 1–26.

Tian, S. and Hamori, S. (2016). Time-varying price shock transmission and volatility spillover in foreign exchange, bond, equity, and commodity markets: Evidence from the united states. *The North American Journal of Economics and Finance*, 38:163–171.

Utsu, T. (1961). A statistical study on the occurrence of aftershocks. *Geophysical Magazine*, 30:521–605.

Weber, P., Wang, F., Vodenska-Chitkushev, I., Havlin, S., and Stanley, H. E. (2007). Relation between volatility correlations in financial markets and omori processes occurring on all scales. *Physical Review E*, 76(1):016109.

WHO (2020). Who coronavirus disease (covid-19) dashboard.

Xu, H.-C., Zhang, W., and Liu, Y.-F. (2014). Short-term market reaction after trading halts in chinese stock market. *Physica A: Statistical Mechanics and its Applications*, 401:103–111.

Zawadowski, Á. G., Andor, G., and Kertész, J. (2006). Short-term market reaction after extreme price changes of liquid stocks. *Quantitative Finance*, 6(4):283–295.

Zhang, D., Hu, M., and Ji, Q. (2020). Financial markets under the global pandemic of covid-19. *Finance Research Letters*, page 101528.