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Climate change and financial stability: Natural disaster impacts on global stock markets

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ABSTRACT

This paper aims to provide a statistical analysis of the impacts of worldwide climate change and consequent natural disasters on international stock markets. By means of a suited event study methodology, we investigate the effects of biological, climatological, geophysical, hydrological and metereological disasters occurred in 104 countries across the world on 27 global stock market indexes over the period 8 February 2001 to 31 December 2019. We find heterogeneous stock markets responses to natural hazard shocks depending on the type of event under consideration, as well as on the location in which the event has occurred. Climatological and biological calamities seem the disaster types which, overall, induce the most extreme reactions of international financial markets. Furthermore, the analysed stock indexes are more responsive to shocks occurring in European countries. Finally, to predictively validate our model, we build a natural disaster risk hedging strategy, which sheds light on the investment opportunities derived from the mitigation of natural risks.

1. Introduction

Financial markets and economic systems are increasingly affected by climate change related events, thereby the emergence of recent research in climate finance — see e.g. [1–4]. The study of risk transmission from natural disasters to the economic and financial systems, are prominent fields of study for current and future research — see, for instance, [5–9]. These approaches have been further expanded to study the nexus between climate change and finance from a wide variety of viewpoints — see [10–12]. For instance, [10] find that banks and investment funds are key players in the low carbon transition via exposures to the same asset classes, highlighting the higher associated risks.

Natural catastrophes can be regarded as non-financial, exogenous shocks to the economy — see e.g. [13–17]. Besides affecting several macroeconomic indicators, they have also direct impacts on domestic financial markets, as well as they exert effects which might reverberate across financial markets of various countries in their neighbourhood or beyond, given the globally interconnected nature of firms and, in general, of financial systems. Their effects might also affect scale-invariance and fractality properties frequently documented in financial market data — see e.g. [18–21].

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Despite the field is relatively novel to researchers, a growing stream of literature deals with the impact of natural disasters on worldwide capital markets. [22] measure, through autoregressive moving average (ARMA) models, the impact of natural disasters on the Australian equity market, employing a record of 42 natural hazards. [23] apply intervention analysis to daily returns on ten market sectors to analyse the effects of natural, industrial and terrorist disasters on the Australian capital market. [24] analyse heteroskedasticity biases based on correlation coefficients to shed light on the contagion effects across 26 international stock indexes and exchange rates due to the strong earthquake occurred in South-East Asia on 26 December 2004.

Within the same literature strand, [25] make use of GARCH models to search for wealth and risk effects of natural disasters on the insurance sector and on the composite stock market indexes returns in Japan and the US while [26] study the long and short run effects of the 2011 Great East Japanese Earthquake on the Japanese equity, debt, FX markets and on Gold price. Within a system generalized method of moments (GMM) framework, [27] study the relationship between four sub-groups of natural disasters, i.e. floods, droughts, storms and earthquakes, and economic growth. [28] discover strong abnormal effects in concomitance with the occurrence of U.S. landfall hurricanes over the period 1990 to 2017 on stock returns. More recently, a stream of research has started focusing on the influence of natural disasters on capital markets from a behavioural perspective, as for instance [29–32].

Furthermore, provided the relative efficiency of stock markets, the impact of natural hazards should be reflected in short-run stock returns. Such abnormal returns provide an expression of the expected variations in future profitability which arise from the occurrence of the hazard. Thus, many financial and behavioural studies have employed event study methodologies to assess the impact of rare disasters on international financial markets, revealing that the negative sentiment due to bad mood and anxiety affects the decision-making process of market participants, which in turn influence asset pricing as in [33,34]. Event study methodologies have been recently used also for determining the impact of natural disasters on international financial markets [see35–37].

Against this background, we develop a comprehensive analysis of the impacts of natural disasters on international capital markets. We investigate the immediate impact of worldwide natural disasters occurred in 104 countries across the world on 27 major and geographic widespread market indexes over the period ranging from 8 February 2001 to 31 December 2019. To this aim, we setup a tailored event study methodology which enables us to investigate two sides of the same coin. Firstly, we examine the effects of five different categories of natural disasters, namely biological, climatological, geophysical, hydrological and metereological, on international stock market indexes. In this way, we are able to determine the type of natural disaster which most largely and widely affects stock market indexes at a global level. Secondly, we study natural disaster impacts on international financial markets by a geographical perspective. Within this framework, we identify which are the territories whose natural calamities exert the harshest impacts on the financial performance of the selected global market indexes.

We contribute to the extant literature regarding the impact of natural disasters on international financial markets in several ways. Differently from most of the earlier research, we do not limit our analysis to domestic natural catastrophes: we analyse the effects of natural hazards occurred during the last two decades across the world on price changes of major and geographic widespread aggregate stock market indexes. To this aim, we tailor our event study methodology to take into account for specific economic and financial dimensions of each country's corresponding financial index, besides controlling for specific time series features. Additionally, we do not only examine the impact of some specific sub-group of natural hazards (e.g. earthquakes), but we exhaustively analyse the impacts exerted by the whole range of natural disaster groups. Finally, we shed some light on the financial contagion effects across international capital markets as a consequence of natural calamities by identifying countries (and continents) whose catastrophic events induce relevant spillover mechanisms in global market indexes.

Furthermore, we contribute to the extant literature by deriving the link between the estimated impacts of natural disasters on worldwide financial markets and the profitability arising from hedging such sources of risk. Within this framework, we propose a statistically grounded natural disaster risk hedging approach, which exploits information on the impact of shocks transmitted from natural disaster occurrences to worldwide stock markets, and we compare it to a benchmark equally weighted investment strategy. Our results show how trading strategies based upon natural hazard risks are sensitive to model parametrizations, nonetheless with several configurations notably outperforming the benchmark in terms of profitability and risk-return profiles.

The remainder of this paper proceeds as follows. Section 2 gives details on the statistical methodology tailored to conduct the event study. In Section 3 we illustrate the data and our preliminary analysis. In Section 4 we present and discuss our empirical outcomes. Section 5 illustrates the empirical outcome of our proposed natural disaster risk hedging strategy. Section 6 concludes.

2. Methodology

To conduct our empirical analysis, we operate within the framework of the Seemingly Unrelated Regression (SUR) models, where a set of regression equations is modelled each having its own dependent variable and potentially different exogenous regressors. In this approach, a fundamental market model is enriched by a dummy variable which assumes the value of 1 when the natural disaster occurs, and zero otherwise. This allows us to express the abnormal returns as regression coefficients. The benefit derived from applying this methodology is twofold. Firstly, it overcomes the abnormal return (AR) dependency by means of estimating a SUR model. Secondly, it enables us to correctly perform hypothesis testing, as the SUR model accounts for eventual heteroskedasticity across equations and contemporaneous correlation among the error terms [38].

Let us consider the continuously compounded returns time series $R_{i,t}$, computed as:

$$R_{i,t} = log(\frac{P_{i,t}}{P_{i,t-1}}) \tag{1}$$

where $P_{i,t}$ and $P_{i,t-1}$ are the prices of the generic market index i at time t and $t-1$, respectively. The ARs can be parametrized by means of the inclusion of an event-day dummy variable in the market model, as follows:

$$R_{i,t} = \alpha_i + \beta_i R_{m,t} + \sum_{t=t_0}^{t_w} \gamma_{i,t} d_t + \epsilon_{i,t} \tag{2}$$

where α_i and β_i stand for the market alpha and beta, respectively, and $R_{m,t}$ represents the long-run return of the aggregate market index at time t, which we compute as the mean of the monthly moving average of the set of individual indexes. The variable d_t is a dummy variable taking the value of 1 if the day t is within the event window $[t_0, t_w]$ and zero elsewhere, with t_0 and t_w being the event date and the last day of the event window, respectively. As a consequence, the generic parameter $\gamma_{i,t}$ represents the AR on market index i at time t comprised in the event window, whereas $\epsilon_{i,t}$ is a zero-mean error term.

In order to quantify the overall reaction of financial indexes following natural disaster events, ARs can be aggregated after the SUR estimation to derive the cumulative abnormal return (CAR) over the event window $[t_0, t_w]$ for each financial index i:

$$CAR_i(t_0, t_w) = \sum_{t=t_0}^{t_w} \gamma_{i,t} \tag{3}$$

The fundamental model presented in Eq. (2) can be extended in several ways in order to correct for overall market shifts, serial correlations and impact of country-specific exogenous regressors. Firstly, we include the interaction term between the dummy variable D_t, which takes the value of 1 during the event window $[t_0, t_w]$ and zero elsewhere, and the market return $R_{m,t}$. This term allows us to control for possible shifts of the overall market returns during the event time window, avoiding possible misinterpretations of the AR coefficients [38,39]. Secondly, we include, in each equation i, k lags[1] of the dependent variable $R_{i,t}$ in order to correct for serial correlation which was found in daily market index returns, detected through the Ljung–Box test. Finally, we include a set of country-specific exogenous variables $\tilde{C_{i,t}}$ to control for changes in the economic and financial conditions of the countries considered in the sample. Hence, our empirical model is formulated as follows:

$$R_{i,t} = \alpha_i + \beta_i R_{m,t} + \beta_i^D D_t R_{m,t} + \sum_{t=t_0}^{t_w} \gamma_{i,t} d_t + \sum_{\tau=1}^{k} \theta_{i\tau} R_{i,t-\tau} + \sum_{n=1}^{n_c} \phi_{i,n} \tilde{C_{i,t}} + \varepsilon_{i,t} \tag{4}$$

As far as control variables are concerned, we consider each country's GDP growth and change in Financial Development Index (FDI) provided by the International Monetary Fund. The rationale behind this choice is that GDP growth accounts for changes in the value of all goods and services produced by an economy, whereas FDI changes measure the variation in a country's depth, access and efficiency of its financial institutions and financial markets. In this way we are able to correct for changes in the country-specific economic and financial dimensions in a parsimonious way. Given that these variables are sampled at a lower frequency with respect to financial indexes data, we use the temporal disaggregation technique proposed by [40], which re-constructs the high-frequency series by solving an optimization problem. In particular, this method builds the high-frequency series as solution of the minimization of the sum of squares of either the first or the second differences of the (unknown) consecutive high-frequency values, under the condition that the annual aggregation of the estimated series adds up the available annual figures.

Hence, we are able to derive higher frequency time series for GDP and FDI which are consistent with their low frequency counterpart. As a consequence, the set of exogenous control variables in our empirical analysis is given by $\tilde{C_{i,t}} = [\tilde{GDP}_{i,t}, \tilde{FDI}_{i,t}]$, with $\tilde{GDP}_{i,t} = log(\frac{GDP_{i,t}}{GDP_{i,t-1}})$ and $\tilde{FDI}_{i,t} = log(\frac{FDI_{i,t}}{FDI_{i,t-1}})$ representing the high-frequency GDP and FDI counterparts.

Our aim is to discover both disaster-specific and location-specific effects on worldwide financial indexes. Thus, we design our regression analysis in a twofold way. Firstly, we consider the impact on the considered financial indexes of all groups of events (i.e. biological, climatological, geophysical, hydrological and metereological), regardless of the country in which the event has occurred. In this case, the parameter $\gamma_{i,t}$ represents the AR on stock index i at time t due to a

[1] We let the number of lags of the dependent variable vary from 0 to 10. We then determine the optimal number of lags to be included in the model through the Bayes–Schwarz information criterion, given that it penalizes overparametrization with respect to similar information criteria such as the Akaike (AIC).

particular category of natural hazard. Secondly, we assess the impact on financial indexes of natural disasters occurred in one specific country, regardless of the type of event. In this case, the parameter $\gamma_{i,t}$ represents the AR on market index i at time t due to events hitting a particular country.

Our approach is similar to the seismological framework adopted for the study of market volatility cascades derived form exogenous announcements [see41,42]. Indeed, in the seismology field, the Omori law concerns the estimate of the Omori power-law exponent which describes the cascade effect of energy propagation following an earthquake. Similarly, in financial markets the same exponents can be estimated to investigate the dynamic relaxation in the volatility or price behaviour of financial assets. In a related context, [43] propose a modelling framework which allows for creating probability predictions on a future market crash in the medium term through Hawkes processes, so to constitute Early Warning Systems (EWSs) for financial markets. In a similar context, [44] study the dynamics of financial contagion by means of ETAS, a class of point processes employed in modelling seismic contagion. We refer the reader to [45] for a comprehensive review of Hawkes processes their applications to finance. In our case, we opt for a more structured model which helps us in discriminating the market effects derived from natural hazards with respect to some control variables, while enabling disaster-specific and country-specific impact analyses.

3. Data description and preliminary analysis

In order to conduct our empirical analysis, we combine different sources of data. Firstly, we analyse the international Emergency Events Database (EM-DAT), constantly updated by the Centre for Research on the Epidemiology of Disaster (CRED), which reports and classify in detail all worldwide natural disasters.[2] We study a set of as much as 6759 natural disasters occurred in 104 countries across the world.[3] Secondly, we analyse daily price returns for 31 major and geographic widespread stock indexes during the period ranging from 8 February 2001 to 31 December 2019. Finally, we retrieve data on the GDP and FDI of each country from the International Monetary Fund (IMF) database.[4]

Natural disasters can be classified according to the type of event identified as the cause of hazard. We study the impact of five main groups of natural disaster, namely biological, climatological, geophysical, hydrological and metereological. As per the international Emergency Events Database, geophysical disasters refer to hazards originating from solid earth. Metereological disasters are hazards caused by short-lived, micro- to meso-scale extreme weather and atmospheric conditions. Hydrological disasters are those hazards caused by the occurrence, movement, and distribution of surface and subsurface freshwater and saltwater. Climatological disasters are hazards caused by long-lived, meso- to macro-scale atmospheric processes ranging from intra-seasonal to multi-decadal climate variability. Biological disasters refer to hazards caused by the exposure to living organisms and their toxic substances (e.g. venom, mold) or vector-borne diseases that they may carry.

In Fig. 1 we illustrate the geographic distribution of worldwide natural disasters, obtained by cumulating each country's event counts for the whole considered set of disaster groups - i.e. biological, climatological, geophysical, hydrological and metereological. The figure shows that China is the country which counts most of the occurrences of natural catastrophes over the considered period. As a matter of fact, it is the country reporting the highest number of both hydrological and geophysical hazards. Straight after China, in the ninth decile of the distribution, we find several American countries. The United States is the country most largely hit by climatological and metereological disasters, together with Mexico and Latin American countries such as Colombia and Brazil, severely hit by geophysical and hydrological calamities. Additionally, South Asian and Pacific countries, such as India, Afghanistan, Pakistan, Iran, Vietnam, Thailand, Philippines, Indonesia and Australia, count a high number of disaster occurrences, along with a few other countries belonging to the European continent, such as Turkey, Italy and France. Additionally, notice that Russia counts a large number of disaster occurrences, mostly metereological and hydrological ones, together with Japan, hardly hit by geophysical and metereological hazards, a few African countries – in particular Nigeria –, which suffer relatively more from biological hazards than other world countries. We refer the reader to Fig. A.1 in Appendix for a disaggregate representation of natural calamities per group of events across the world.

In order to investigate the impact of natural disasters on aggregate stock markets, we select daily price returns from 31 major and widespread stock indexes which geographically cover a considerable portion of the globe. Before moving forward with our analysis, we investigate whether such market indexes exhibit serial correlations in the examined price series, i.e. the assumption of the stock market not being a random walk. In this context, no abnormal returns should be gained by studying the information contained in historical prices [46]. In Fig. A.2 in Appendix we illustrate the empirical outcomes of the non overlapping multi-period variance test for the selected market indexes for two selected lag orders, i.e. $\lceil log(T) \rceil = 9$ and 20, as it is commonly used in empirical analysis. Considering both lag orders, the test provides strong evidence on the non-randomness of the Kenya NSE 20 index returns, whereas the test rejects at a 5% significance level the null hypothesis of a random walk behaviour of the return series associated to the S&P Merval and CROBEX indexes

2 See https://www.emdat.be/ for more details on the international Emergency Events Database.

3 For the sake of representativity, we consider only those countries which reported more than 25 events during the considered sample period from 8 February 2001 to 31 December 2019. We refer the reader to Table A.1 in Appendix for a comprehensive list of the analysed countries.

4 See https://data.imf.org/ for more details on the data.

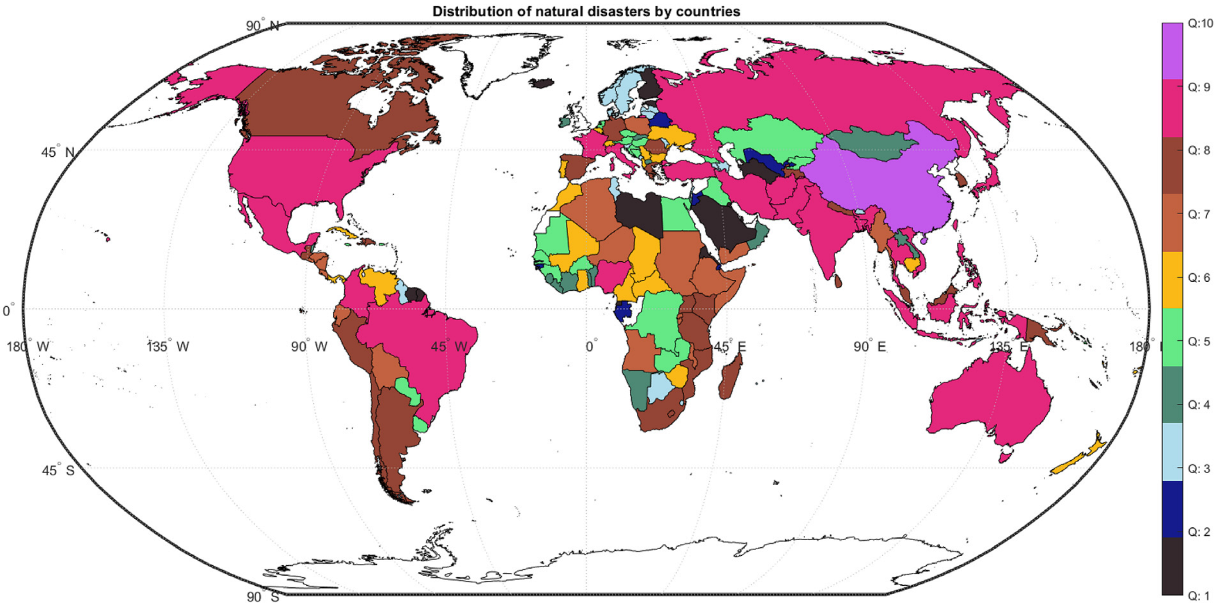

Fig. 1. The geography of natural disasters. The figure shows the geographical distribution of the number of worldwide natural disasters occurred during the period 8 February 2001–31 December 2019. Colours represent the deciles of the distribution of natural disaster counts.

– with a lag order of 9 - and that of Karachi 100 – with a lag order of 20. Thus, we find a weak form of inefficiency of these markets, which induces us to exclude the aforementioned indexes from the subsequent empirical analysis.

In Table 1 we illustrate summary statistics for the selected stock market indexes while we refer to Fig. A.3 in Appendix for the return distribution of the market indexes. As expected, the return distributions of stock indexes are generally centred around zero. Over the investigated period, market index returns range from a minimum of −18.66% to a maximum of 28.69%, both registered in the MOEX Russia index. The average daily returns are in all cases positive and close to zero, with the one deviating at most (least) from 0 being the MOEX Russia index (the Dutch AEX index), whereas the highest (lowest) volatility registered is that of the Turkish BIST 100 index (the Chilean S&P CLX IPSA). Note that the majority of the returns distributions are moderately skewed right (18 out of 27), with the US Nasdaq 100 (Thailand SET Index) being the most right- (left-) skewed index. Overall, the kurtosis of return distributions ranges from a minimum of 5.67 (related to the Polish WIG20) and a maximum of 22.68 (related to the MOEX Russia index), which provides evidence of a generally leptokurtic behaviour with respect to a benchmark normal distribution.

4. Empirical results and discussion

We present our empirical results as follows. In the first Subsection, we examine the impact of each type of natural disaster on the performances of each market index. In the second Subsection, we illustrate how ARs vary according to the geographical location of the natural hazards.

4.1. Disaster-specific impact analysis

We analyse the impact on the price dynamics of the selected market indexes of natural disasters according to their category — biological, climatological, geophysical, hydrological and meteorological. In other words, we estimate a set of five regression equations per index from Eq. (4), where each dummy variable represents one of the five sources of hazards under consideration.

Fig. 2 shows the kernel densities of the estimated CAR associated to the impact of natural disasters by type of event, estimated over the whole sample period. We address the reader to Fig. A.4 in Appendix for an illustration of the kernel densities of the $\gamma_{i,t}$ regression coefficients associated to the impact of each source of natural shock for t periods ahead the occurrence of the event. Overall, CAR distributions show peaks around the value of 0, with an overall slightly higher degree of concentration in the left part of the distribution. This suggests that there is asymmetry between positive and

Table 1
Descriptive statistics.

Country	Index	Min	Max	Mean	Std	Skew	Kurt
Australia	S&P ASX 200	−8.34	5.79	0.013	0.96	−0.39	8.73
Belgium	BEL 20	−7.98	9.78	0.011	1.22	0.12	9.85
Brazil	Bovespa	−11.39	14.66	0.051	1.72	0.02	7.71
Canada	S&P TSX Composite	−9.32	9.82	0.013	1.08	−0.49	13.00
Chile	S&P CLX IPSA	−6.92	12.53	0.034	0.96	0.21	13.92
Denmark	OMX Copenhagen 20	−11.06	9.96	0.033	1.25	−0.14	8.68
Finland	OMX Helsinki 25	−8.52	14.24	0.026	1.39	0.22	9.20
France	CAC 40	−9.04	11.18	0.008	1.43	0.10	8.42
Germany	DAX	−8.49	11.4	0.024	1.46	0.10	8.28
Hong Kong	Hang Seng	−12.7	14.35	0.019	1.42	0.21	12.79
India	Nifty 50	−12.24	17.74	0.052	1.45	−0.06	13.11
Indonesia	Jakarta Stock Exchange	−10.38	7.92	0.050	1.33	−0.49	9.28
Mexico	S&P BMV IPC	−7.93	11.01	0.047	1.26	0.15	9.23
Netherlands	AEX	−9.14	10.55	0.004	1.40	0.10	10.16
Norway	OSE Benchmark	−9.95	10.67	0.043	1.42	−0.35	9.92
Poland	WIG20	−8.1	8.5	0.011	1.48	−0.07	5.67
Russia	MOEX Russia	−18.66	28.69	0.063	2.00	0.36	22.68
South Africa	South Africa Top 40	−8.05	8.01	0.052	1.29	0.01	6.47
South Korea	KOSPI	−12.02	11.95	0.025	1.49	−0.42	9.42
Spain	IBEX 35	−9.14	14.43	0.006	1.45	0.26	8.73
Sweden	OMX Stockholm 30	−8.42	10.37	0.013	1.49	0.11	7.02
Switzerland	SMI	−7.79	11.39	0.016	1.15	0.03	9.88
Thailand	SET Index	−14.84	11.16	0.042	1.30	−0.55	12.39
Turkey	BIST 100	−18.11	19.44	0.059	2.09	0.24	11.40
United Kingdom	FTSE 100	−7.85	9.84	0.006	1.15	0.08	9.77
United States	NASDAQ Composite	−9.67	14.17	0.018	1.57	0.22	9.69
United States	Nasdaq 100	−10.52	18.77	0.022	1.76	0.46	11.47

The table shows the descriptive statistics of the financial indexes returns (expressed in percentage terms) during the period 8 February 2001–31 December 2019, along with their reference countries.

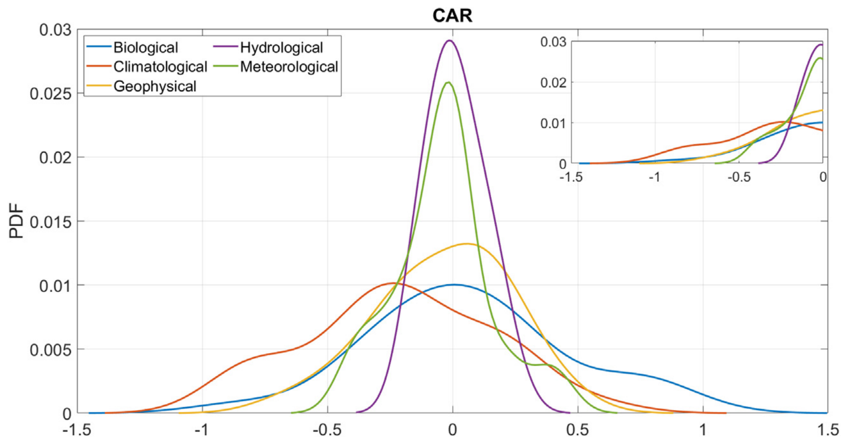

Fig. 2. Kernel densities of the estimated CARs. The figure shows the kernel densities of the estimated cumulative abnormal returns $CAR(t_0 = 0, t_w = 4)$ associated to the impact of each source of natural shock.

negative impacts of natural disasters on global financial markets, with negative effects being more frequently observed than positive ones.

In general, the natural catastrophe types which impact the most the financial markets turn out to be the climatological and biological ones, which exhibit flatter distributions if compared to those of the other natural disaster classes. Interestingly, we find that impacts of biological and climatological disasters behave dissimilarly in their left and right distribution tails: evidence supports the fact that, overall, biological events tend to generate more positive effects on market indexes than negative ones, while climatological events affect stock returns more severely in a negative way. This

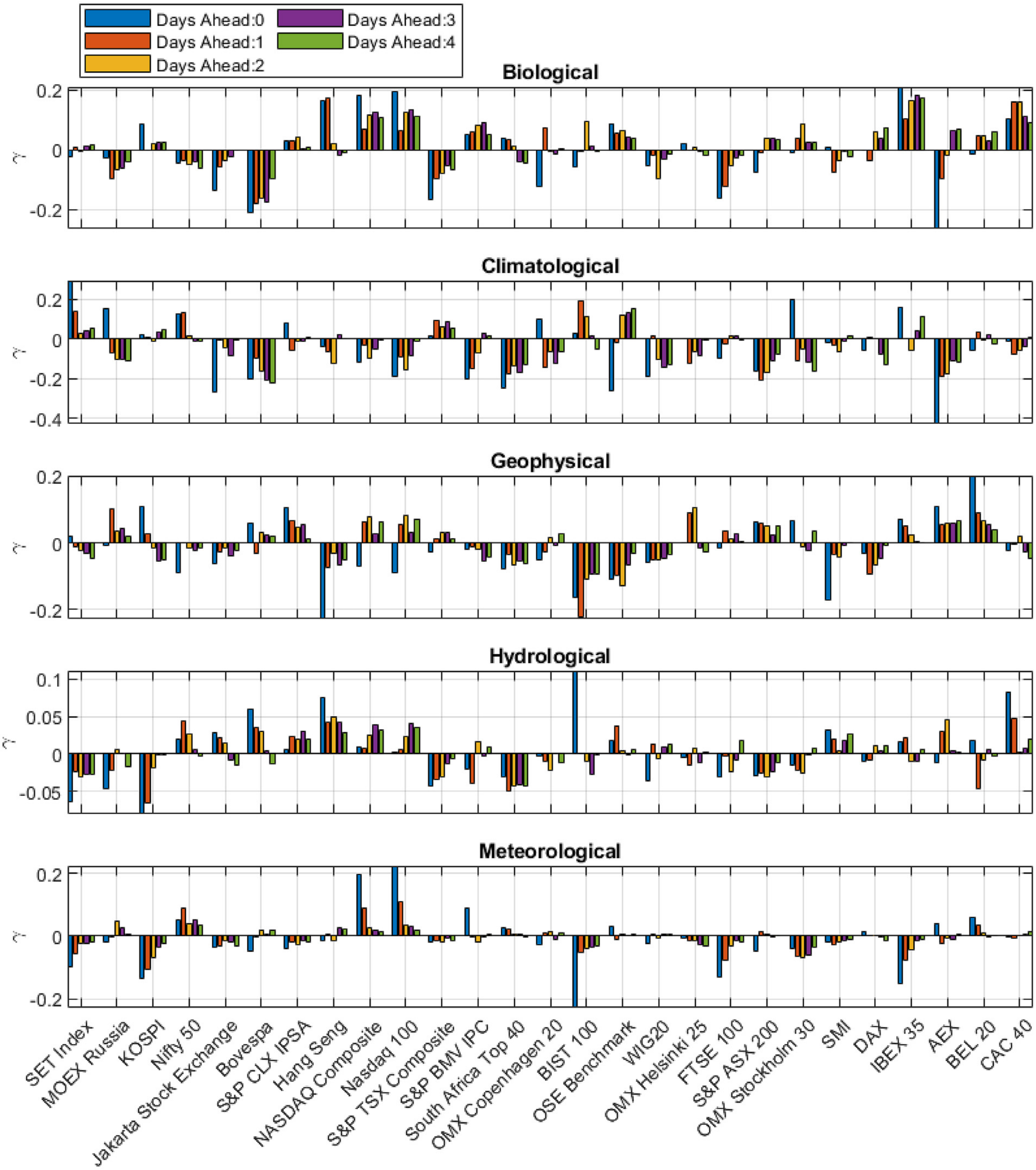

Fig. 3. AR estimates The figure shows the estimates of the $\gamma_{i,t}$ regression coefficients associated to the impact of biological, climatological, geophysical, hydrological and meteorological events for the selected stock indexes, with $t = 0, 1, 2, 3, 4$ being the step ahead the event date.

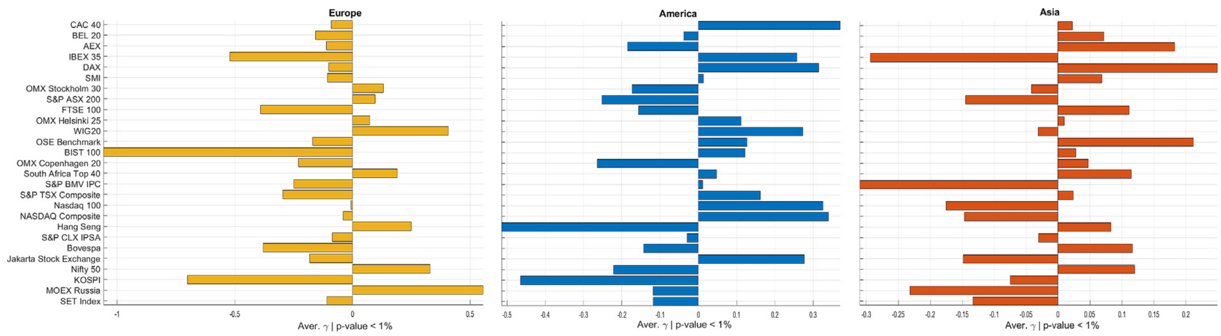

Fig. 4. Estimated average ARs from natural disasters in Europe, America and Asia. The figure shows the estimated average $\gamma_{i,t}$ associated to natural disasters occurring in European, American and Asian countries by market index. We consider the average of statistically significant effects, namely those coefficients reporting a p-value which is less than 1%.

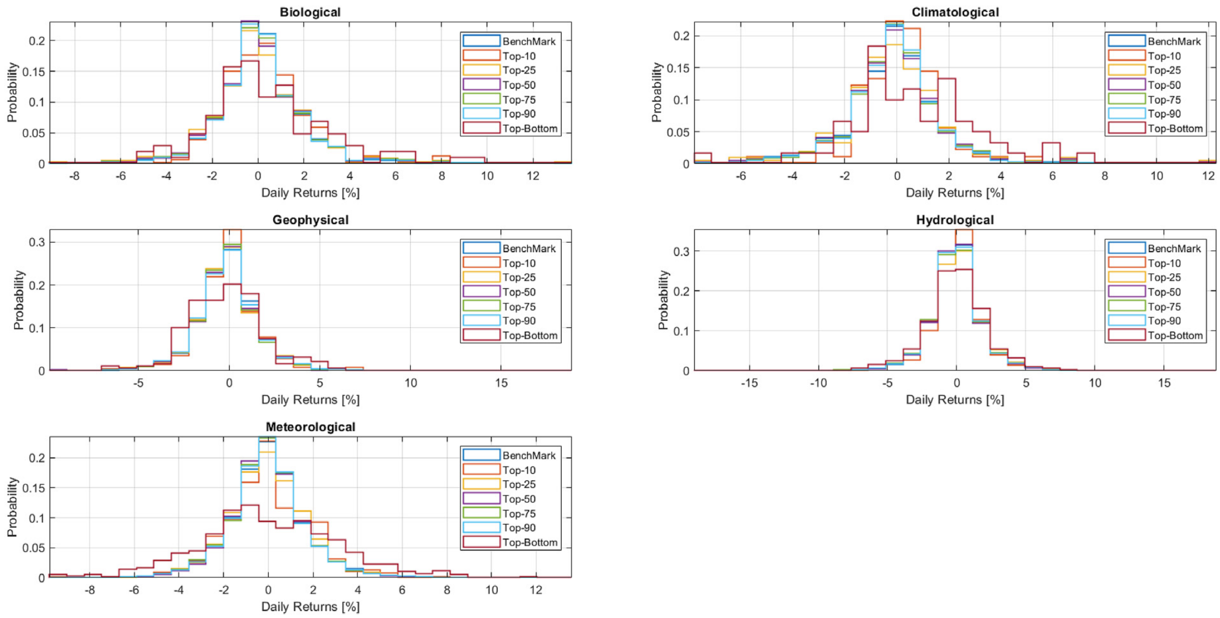

Fig. 5. Distribution of the returns of different risk hedging strategy. The figure reports the probability distribution function of the returns obtained with different top–bottom portfolios which hedge against specific natural hazard.

is allegedly due to the fact that biological hazards have mostly hit developing regions, such as African countries – see in Fig. A.1 the Republic of Congo and Kenya – and, to a lesser extent, Southern Asian ones – see India –, whose impact on the dynamics of financial indexes of developed countries is relatively weak. Conversely, climatological events are frequently observed in developed countries and world powers – see the US, China and Russia –, where negative financial effects are more likely to spread on a global scale.

Climatological and biological hazards are followed – in terms of severity of their impacts – by geophysical events, whose tail in the CAR distribution is considerably longer than that of the remaining classes of hazards, especially in the left part of the distribution. Finally, the impacts of meteorological and hydrogeological events appear to be less pronounced if compared to the previously mentioned natural disasters, with the former showing an evident flatter left tail with respect to the right one.

Table 2
Natural disaster risk strategy return performance.

Disaster type	Bench.	Top-10	Top-25	Top-50	Top-75	Top-90	Top/Bottom
Biological	0.062	0.118	0.032	0.024	0.052	0.066	0.088
Climatological	−0.017	0.121	0.001	−0.044	−0.025	−0.027	0.066
Geophysical	0.022	0.048	0.008	0.024	0.017	0.019	0.007
Hydrological	0.038	0.034	0.035	0.030	0.025	0.034	−0.041
Meteorological	0.032	0.062	0.041	0.039	0.026	0.035	0.054
Total	0.137	0.384	0.118	0.074	0.095	0.128	0.174

The table shows the average daily returns in percentage of strategies which account for the sensitivity to natural disasters of world indexes from 8 February 2014 to 31 December 2019. The table reports figures for several percentile portfolios: 10-th, 25-th, 50-th, 75-th, 90-th. Percentile portfolios are redefined each in-sample window and the corresponding 500-day out of sample return time series are stacked to form a full sample period for each percentile portfolio on which we calculate summary statistics. *Top/Bottom* is the portfolio obtained opening long positions in the best-performer decile indexes and short ones in those belonging to the worst-performer decile.

To illustrate, within the considered sample period, the estimated harshest geophysical event occurred in terms of economic damages is the Great East Japan Earthquake (and consequent tsunami) of 2011, which has been classified as the most powerful earthquake ever recorded in Japan, as well as one of the most powerful earthquake in the world since the last century: it translated into estimated economic losses of roughly 210 billion USD.[5] These losses were almost two times larger than those due to the sharpest meteorological hazard, the hurricane Katrina, which caused over 125 billion USD.[6] in damage in August 2005, as well as more than five times larger than the most devastating hydrological events, i.e. the series of floods occurred during the 2011 monsoon season in Thailand, whose estimated damages are determined in approximately 40 billion USD[7]

Fig. 3 reports the estimated $\gamma_{i,t}$ for the selected market indexes. We also report in Fig. A.5 of the Appendix their associated t-test statistics in absolute values, which we consider statistically significant when they exceed the 90% confidence level.

Biological disasters feature a mixed effect on the selected market indexes. On the one hand, the AR coefficients associated to the Brazilian Bovespa index are negative and statistically significant a few days after the event day. This is arguably because of the sensitivity of the country population to viral diseases, such as the dengue infection and yellow fever outbreaks in the Americas during the last two decades. On the other hand, the IBEX 35 and CAC 40 indexes – and, to a lesser extent, the Nasdaq indexes – show significant positive effects towards biological events. This suggests that financial protection towards this kind of natural risk might be achieved by investing in selected developed country indexes, such as those belonging to Europe and North America.

Consistently with their CAR distribution, climatological disasters mainly exert negative impacts on financial markets. The highest negative and statistically significant impact is that of climatological events on the Australian S&P ASX 200. Land fires, forest fires and droughts were indeed frequently observed in the country, some of which brought devastating economic consequences, such as the Currowan fire in 2019, whose estimated total damage amounts to 2 billion USD. Additionally, the lack of positive and significant AR coefficients, in line with the estimated CAR distribution, indicates that this risk can be hardly offset by investing in other countries' financial indexes, leading to the fact that climatological disasters arguably constitute not only the most severe source of natural shocks, but also a source of systemic risk, being one of the most difficult to hedge.

The majority of geophysical events impact financial markets in a negative way. The largest significant negative effect is that on the Hong Kong Hang Seng index. China is indeed the country which suffered the largest number of geophysical hazards during the considered period, many of which caused devastating economic impacts. A prominent example is the 2008 Sichuan earthquake, a 8.0 Richter scale ground movement whose damages to the Chinese economy are estimated in 85 billion USD. Among others, evidence shows that the BEL 20 index might be useful to diversify risks arising from geophysical calamities, as impacts of these natural hazards are found to be positive and significant, at least at the event date. To illustrate, only two geophysical events have been observed in Belgium since 1900 (none of the two within our sample period), i.e. the 1983 and 1992 earthquakes, qualifying the country as a relative aseismic one, with direct consequences on the potential to hedge geophysical risk.

Hydrological disasters, on the other hand, exert a mixed effect on worldwide market indexes. However, both positive and negative impacts are not statistically significant when considering 95% and 99% confidence levels. This translates

5 The Great East Japan Earthquake of 2011, besides others, damaged many chemical installations, including a refinery which was inundated by the tsunami originating a structural damage. Storage tanks containing sulfur, asphalt and gasoline caught fire. Source: Chemical releases caused by natural hazard events and disasters, WHO (2018): https://reliefweb.int/report/world/chemical-releases-caused-natural-hazard-events-and-disasters-information-public-health.

6 The combination of storms and high winds occurred during hurricane Katrina generated oil spills from refineries, releases of diesel fuel from tanks, waste sites and abandoned vehicles, as well as remobilization of soil contaminants. Source: Chemical releases caused by natural hazard events and disasters, WHO (2018): https://reliefweb.int/report/world/chemical-releases-caused-natural-hazard-events-and-disasters-information-public-health.

7 Estimates of the total damages (USD) caused by natural catastrophes expressed are those according to the EM-DAT database.

into a resilience of stock markets to shocks due to hydrological hazards such as floods and landslides. As a consequence, hedging against hydrological disaster risks is relatively difficult when investing, though it is also arguably not so beneficial in terms of investment performances, given their relatively lower impact on aggregate stock markets with respect to other types of natural hazards.

Metereological disasters affect stock market returns more negatively than positively, as also confirmed by the associated CAR distribution, which exhibit a clear hump in its negative part. The most negative impacts are those observed on the BIST 100 and IBEX 35 indexes, which however tend to fade away after the event has occurred. As a prominent example, dreadful storms and extreme temperatures have hit Spain not very frequently but rather severely over the last two decades.[8] Evidence also suggests that the Nasdaq Composite and Nasdaq 100 indexes react positively when meteorological calamities occur. Hence, in order to mitigate meteorological risks, it seems convenient to invest in technological sector indexes such as the Nasdaq Composite or Nasdaq 100, whose stock composition and geographical coverage enhance resilience to shocks arising from meteorological hazards.

4.2. Location-specific impact analysis

In this Subsection we analyse the impact of natural disasters occurring in a country on the dynamics of the selected stock indexes. Within this framework, we perform a set of N regressions as in Eq. (4), with N being the number of countries considered. The associated dummy variables take on the value of 1 if a natural hazard has occurred within the country at that point in time, and zero otherwise. In this setting we obtain, for each considered market index, an estimate of the ARs caused by the occurrence of natural calamities in each world country. In order to provide a comprehensive overview of the AR dynamics across market indexes and countries, we present aggregate results by continents in which events have occurred (see Figs. A.6–A.7 in Appendix for country/index specific results). To address the location-specific impact analysis, we consider the impact of natural disaster shocks occurred in Europe, America and Asia. This is illustrated in Fig. 4, where we show the estimated average CARs caused by natural disasters occurring within the selected continents for each of the selected stock indexes. We average across highly statistically significant AR coefficients, i.e. those with a t-test not exceeding the threshold of 1% significance level. We address the reader to Fig. A.8 in the Appendix for the results related to Africa and Oceania.

The magnitude of the average CAR coefficients associated to natural disasters occurring in world continents shows that market indexes respond heterogeneously to natural shocks depending upon the countries in which they take place. Indeed, it seems that the selected worldwide stock indexes are impacted in a pronounced way from natural disasters occurring in European countries, followed by natural disasters in America and, finally, in Asia. Additionally, while natural calamities taking place in America and Asia appear to be quite balanced in terms of positive and negative effects, the ones occurring in Europe tend to negatively impact market indexes. Evidence additionally shows the global and interconnected nature of financial markets. Indeed, a stock index of a given country is not only affected by domestic catastrophic events, but it also suffers from natural disasters which hit geographically distant territories.

On the one hand, results show that natural disasters occurring in Europe largely affect the dynamics of the Turkish BIST 100 index in a negative way. Besides the effects of natural catastrophes on the domestic financial market, this might be due to the large fraction of index components with businesses running all over Europe (and beyond) related to sectors which are sensitive to natural shocks. For instance, within the first ten stocks in terms of market capitalization as of 21 December 2020, we find Gersan Elektrik, Anel Elektrik, Park Elektrik, operating in the Electricity sector, Metro Holding and GSD Holding, operating in the energy sectors, among others. Additionally, the Spanish IBEX 35 is negatively impacted by natural shocks occurring in Europe, as well as on those hitting Asian countries. The Spanish index counts several utilities components, such as Iberdrola and Endesa and Naturgy Energy Group, which mainly deal with production and distribution of natural gas, electricity and renewable energy and operate directly or through subsidiaries in many countries in Europe – such as Spain, Germany, Portugal, Italy, and France the United Kingdom – among others. This allegedly fosters the sensitivity of the stock index to natural calamities happening in strategic countries for the companies' businesses. A similar consideration applies to the Korean KOSPI index, whose global business firms operating overseas make it sensitive to disasters occurring in business strategic locations, such as Europe and America. For instance, the most capitalized company in that index is Samsung Electronics, a global company with assembly plants and sales networks in 74 countries which, together with Samsung Biologics and Samsung SDI, is in the top ten most capitalized index constituents, along with many other technological companies operating beyond national borders.

On the other hand, we also find that some of the market indexes respond, on average, quite positively to natural disasters taking place in European countries. This is the case of the MOEX Russia index. Indeed, oil and gas constitute a massive proportion of Russian production and exports and, as illustrated by Eurostat reports, Russia has maintained its position as the leading supplier to the EU of the main primary energy commodities, i.e. hard coal, crude oil and natural gas, over the period from 2007 to 2017,[9] besides being the largest supplier of natural gas to the EU, both in 2019 and

[8] See, for instance, the 2009 exceptional winter storm over northern Iberia and southern France – the so called Klaus cyclone – which caused massive damages to properties and major forests in the Spanish country, and the European heat wave of 2003, which affected a significant portion of western Europe, with Spain counting more than 15,000 deaths.

[9] Source: Energy production and Imports. Eurostat. https://ec.europa.eu/eurostat/statistics-explained/index.php/Energy_production_and_imports.

2020.[10] Hence imports of such products are nowadays vital for the EU countries as far as energy supply is concerned, which implies also the Russian Federation's self-sufficiency in this regards. This allegedly immunizes the country from natural disaster shocks occurring in Europe, enhancing its potential to diversify the risk of natural hazards taking place in the old continent.

For what concerns natural hazards in America, results show that they exert a relatively large negative impact on the Hang Seng index and the KOSPI. The negative influence of these natural hazards on the Korean index is allegedly due to the market interrelationships of Korean companies with the Americas. For instance, Samsung Electronics has had among its largest clients the well-known American companies Apple Inc., Dell, Helwett-Packard, Verizon Communications and AT&T Inc.

Other market indexes, instead, react positively to natural calamities occurring in American countries. Among the largest positive impacts we find those on the French CAC 40 and the German DAX. As a matter of fact, within the top energy producers of the EU we find France, which leverages on nuclear power, and Germany, which owns a considerable share of renewable energy and solid fossil fuels production.[11] This poses the two countries in a favourable position with respect to a large fraction of EU countries, which, in contrast, rely on imports from foreign countries — many of which located in the Americas.[12] - in a more pronounced way. Surprisingly, we find also a large positive impact of natural hazards occurring in the Americas on the US Nasdaq 100 and Nasdaq Composite. This is arguably due to the concentration in the indexes of stocks belonging to the technological sector, making them resilient to shocks arising from natural disasters. Hence, all the aforementioned indexes might be instrumental to hedge risks coming from natural hazards taking place in American countries.

Natural disasters hitting Asian countries exert a severe negative impact on the Mexican index, i.e. the S&P BMV IPC, and the Spanish IBEX 35. Latin America's second largest economy in terms of GDP at purchasing power parity (PPP) has gradually worked towards a diversification of its trade to reduce its dependence on the US market. For years, what was a peripheral market for Mexico, i.e. the Asian continent, has been growing in importance, driven by a robust demand in the Orient for Mexican goods. This has strengthen the ties between the country and the East, resulting in the reflection of natural hazard consequences on its market index performance. Notice that also the MOEX Russia index responds in a negative way to natural calamities located in the Asian continent. Recalling that the same AR coefficients related to the European countries effects are positive, this can be interpreted as a result of the tighter integration of the Russian Federation with the Asian world, rather than the European one, allegedly fostered by the West's sanctions against Russia which positively influences the export volume to East Asia. The positive impacts observed for DAX and OSE Benchmark likely emerge for the analogous reasons concerning the primary energy production formerly discussed. Indeed, Norway is one of the largest producer of oil and natural gas in Europe, thus being relatively independent from the occurrence of natural hazards in Asian countries.

5. Natural disaster risk hedging strategy

To predictively validate our model, we build a natural disaster risk hedging strategy, which sheds light on the mitigation opportunities of natural risks. All of the findings reported so far consist of a measurable quantification of the price information spillovers due to the occurrence of natural catastrophes. It is therefore worth to investigate whether the model correctly forecasts the market index movements once a natural shock has occurred.

From these premises, we setup a simple investment strategy to show opportunities of profitable trades by hedging natural disaster risk. Our strategy takes root from the statistical information derived by the AR coefficient estimates, which represent the impacts of natural disasters on stock indexes in the market model. This impact can be conceived as a factor in the market model, whose coefficient provides relevant statistical information on the sensitivity of market indexes to each type of natural disaster risk.

To this aim, we propose a portfolio selection approach based on: (i) a statistical measurement of the portfolio beta, with takes into account the sensitivity of stock markets to natural hazards; (ii) a top–bottom investment strategy, as an alternative portfolio construction approach to account for different natural hazard reactivity of single financial indexes.

The trading strategy is back-tested using a walk forward approach. We opt for an in-sample data time window of 3000 daily observations and we compute the rolling betas and top–bottom portfolio performances over the next 500 days, i.e. portfolio re-balancing is computed every 500 days (roughly two trading years). The in-sample time window is subsequently shifted forward by the period covered by the out of sample test, and the portfolio allocation algorithm is repeated. Results are used to assess the daily performance of the top–bottom trading strategy over the period ranging

[10] Source: EU imports of energy products — recent developments. Eurostat. Retrieved 15 October 2020. https://ec.europa.eu/eurostat/statistics-explained/pdfscache/46126.pdf.

[11] To illustrate, in 2017, the whole primary energy production across the EU member states was the largest in France, where a 17.4% share of the EU-28 total was produced, followed by the United Kingdom (15.6%) and Germany (15.3%). Source: Energy, transport and environment statistics, Eurostat (2019): https://ec.europa.eu/eurostat/documents/3217494/10165279/KS-DK-19-001-EN-N.pdf/76651a29-b817-eed4-f9f2-92bf692e1ed9.

[12] To illustrate, Colombia, US and Canada are among the top primary energy exporters to the EU 28 countries over the period 2007–2017, in particular for what concerns hard coal. Source: Energy, transport and environment statistics, Eurostat (2019): https://ec.europa.eu/eurostat/documents/3217494/10165279/KS-DK-19-001-EN-N.pdf/76651a29-b817-eed4-f9f2-92bf692e1ed9.

from 8 February 2014 to 31 December 2019, from which we extrapolate relevant summary statistics on their risk-return profiles.

Our trading strategy is based on top–bottom portfolios created by firstly estimating model in Eq. (4) and, secondly, by selecting as top stocks those having γ value higher than the kth percentile of the γ-distribution, while as bottom ones those with γ being lower than the $(100 - k)$-th percentile. On the one hand, stocks belonging to the top portfolio exhibit both increasing past trends and predicted positive price trends, signalling a strong bullish market phase. On the other hand, stocks composing the bottom portfolio are those reporting both decreasing past and forecasted price trends, hence representing a strong but negative market trend. We then compute profits and losses of each portfolio given their open long positions on top stocks and open short positions on bottom stocks.

As a benchmark for our analysis, we compare the performances of the proposed investment strategy with those achieved by an equally weighted portfolio, i.e. a portfolio whose weights are constant and equally distributed across the 27 international stock indexes. Table 2 compares the average returns of the benchmark equally weighted and natural risk top–bottom portfolio strategies over the period from 8 February 2014 to 31 December 2019, while Fig. 5 shows the strategies' returns distributions.

The Top-10 strategy is the one yielding to the highest performances in terms of average returns, with an almost three times larger average return if compared to the benchmark equally weighted portfolio. Notice also that the Top/Bottom trading strategy achieves, on average, greater returns than the benchmark strategy. With the increasing number of stock indexes as a result of increasing the top-percentile, the top-strategy does not yield greater performances with respect to benchmark, though the effect is non-monotone — see the dynamics of Top-25, Top-50, Top-75 and Top-90, jointly.

Table 2 also offers some relevant insights on the capability of each strategy in generating extra-returns by considered sources of natural shocks. Evidence shows that the two best strategies (Top-10, Top/Bottom) notably overperform the benchmark in terms of returns generated by biological and climatological and metereological risk factors. While the Top/Bottom strategy does report lower performances with regards to geophysical and hydrological disasters, the Top-10 strategy still achieves greater average returns than the benchmark when accounting for geophysical hazard risks, and though lower still comparable performance for hydrological ones (0.038 against 0.034). To comprehensively measure the actual risk-return profiles of our set of top–bottom portfolios, we also compute Sharpe ratios. Results are reported in Table A.4 of Appendix.

6. Concluding remarks

In this paper we have built a comprehensive study of the impacts of climate change and consequent natural disasters across the world on international capital markets. Indeed, we have developed a tailored event study methodology in order to examine the impact of natural disasters occurred in 104 countries across the world on 27 global market indexes. Our empirical analysis offers two main streams of investigation. Firstly, we have studied the impacts of five different groups of natural disasters – i.e. biological, climatological, geophysical, hydrological and metereological – on the performance of international stock market indexes. Secondly, we have investigated how the geographical distribution of natural disasters around the globe had specific impacts on stock market indexes.

We have found heterogeneity in stock market responses to natural disaster shocks depending on the type of event under consideration. In particular, evidence shows that climatological and biological hazards are the ones showing the harshest impacts on international financial markets returns, immediately followed by geophysical events. However, while climatological catastrophes tend to affect financial markets mostly in a negative way, biological ones tend to generate more positive responses on the selected set of financial indexes. On the other hand, we have discovered that metereological and hydrological catastrophes have weaker effects on the performance of global market indexes. Furthermore, we have identified several positive and negative responses to the different types of natural hazards which could potentially enhance investors' diversification benefits towards specific groups of natural calamities.

In addition, we find diverse responses of stock market performances due to natural hazards occurring in specific countries. We have discovered that the investigated stock market indexes are particularly sensitive to shocks occurring in countries belonging to the European continent, which, overall, tend to affect in a negative way their performances.

We have also found significant spillover effects among market indexes and natural disasters belonging to different territorial areas, which we have shown, by means of a top–bottom portfolio approach, to be useful to market participants to hedge the risk arising from the occurrence of natural catastrophes affecting the risk-return profiles of their equity portfolio.

We remark that climate change and related financial and economic risks should be re-evaluated in light of the COVID-19 pandemic, which has exerted dramatic impact on both the economic and financial dimensions of countries — see e.g. [41,47]. On the other hand, most of the market dynamic was allegedly not directly impacted by the evolution of the epidemics, but, instead, by restrictions, economic projections and financial stimulus and announcements, such as those related to the US shown for illustrative purposes in Table A.3 in Appendix - see [41] for more details on such impacts.

Future research directions in this field may include different modelling paradigms. In particular, the market reaction to natural disaster events can be evaluated through the market connectedness framework of [48,49] and, more in general, by means of network models and statistical physics — see [50–53]. These tools have been widely employed to measure return and volatility spillover across stationary or non-stationary and co-integrated financial instruments – see for instance [54–57] –, and to build network-augmented and statistical physics-based asset allocation and trading strategies — see, for example, [58–60]. This paves the way to new modelling frameworks which can help mitigating losses and risks due to climate change and natural hazards.

CRediT authorship contribution statement

Paolo Pagnottoni: Conceptualization, Investigation, Methodology, Software, Data curation, Writing – Original draft preparation, Writing – review & editing. **Alessandro Spelta:** Conceptualization, Investigation, Methodology, Software, Visualization, Data curation, Writing – original draft preparation, Writing – review & editing. **Andrea Flori:** Conceptualization, Investigation. **Fabio Pammolli:** Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix

A.1. Additional data description and preliminary analysis

See Tables A.1–A.3 and Figs. A.1–A.3.

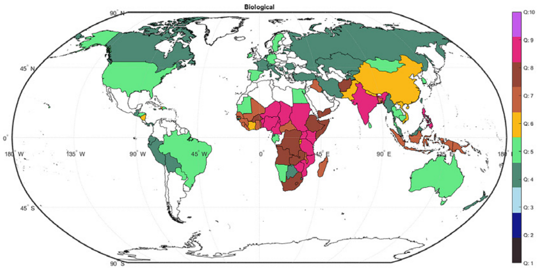
A.2. Additional results

See Figs. A.4–A.8 and Table A.4.

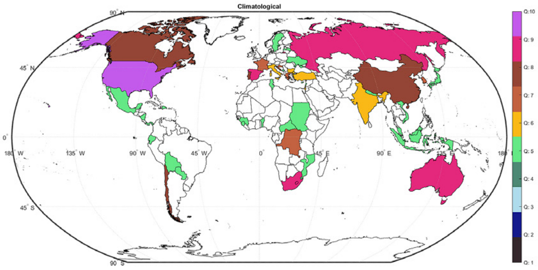
Table A.1
List of selected countries.

Afghanistan	Côte d'Ivoire	Kyrgyzstan	Saudi Arabia
Albania	Dominican Republic	Libya	Senegal
Algeria	Ecuador	Madagascar	Serbia
Angola	Egypt	Malawi	Sierra Leone
Argentina	El Salvador	Malaysia	Somalia
Australia	Ethiopia	Mali	South Africa
Bangladesh	Fiji	Mauritania	Spain
Belgium	France	Mexico	Sri Lanka
Benin	Germany	Morocco	Sudan
Bolivia	Ghana	Mozambique	Switzerland
Brazil	Greece	Myanmar	Syrian Arab Republic
Bulgaria	Guatemala	Nepal	Taiwan
Burkina Faso	Guinea	New Zealand	Tajikistan
Burundi	Haiti	Nicaragua	Tanzania, United Republic of
Cambodia	Honduras	Niger	Thailand
Cameroon	Hungary	Nigeria	Tunisia
Canada	India	Pakistan	Turkey
Central African Republic	Indonesia	Panama	Uganda
Chad	Iran	Papua New Guinea	Ukraine
Chile	Iraq	Peru	United Kingdom
China	Italy	Philippines	United States of America
Colombia	Japan	Poland	Venezuela
Congo	Kazakhstan	Portugal	Viet Nam
Congo	Kenya	Romania	Yemen
Costa Rica	Korea	Russian Federation	Zambia
Cuba	Korea	Rwanda	Zimbabwe

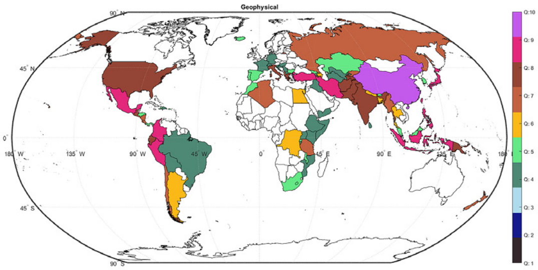
The table shows the list of 104 selected world countries of which natural disaster events are considered.



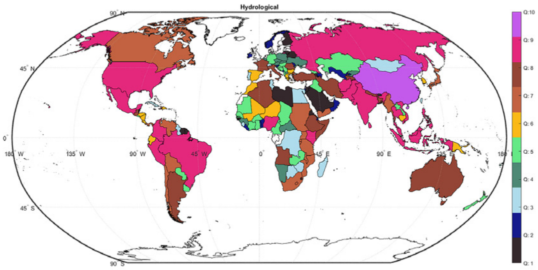
(a) Biological



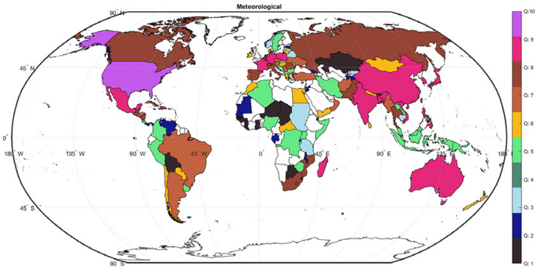
(b) Climatological



(c) Geophysical



(d) Hydrological



(e) Meteorological

Fig. A.1. The geography of natural disasters. The figure shows the geographical distribution of the number of worldwide natural disasters occurred during the period 8 February 2001–31 December 2019. Colours represent the deciles of the distribution of natural disaster event counts associated to each natural disaster type.

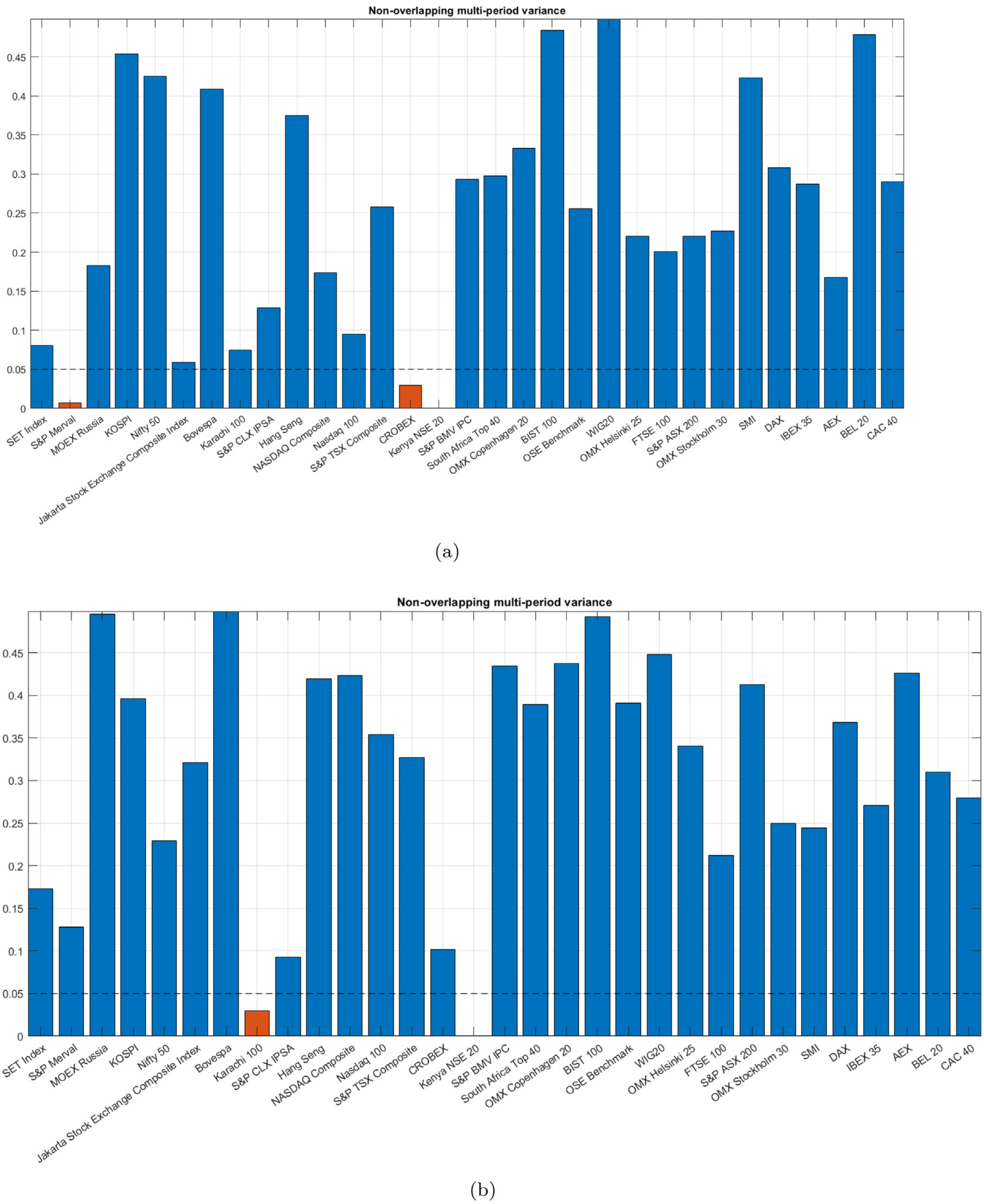
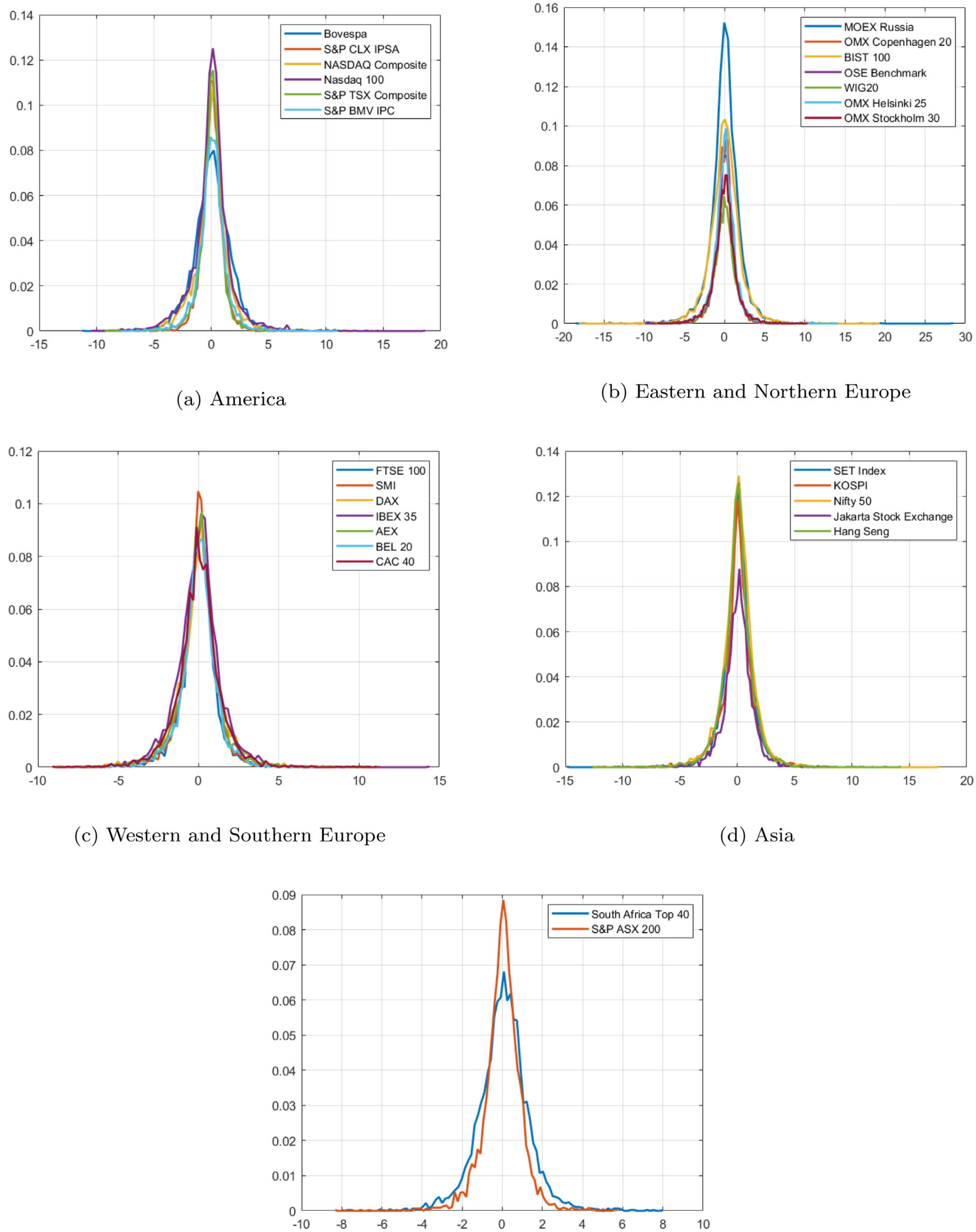


Fig. A.2. Non overlapping multi-period variance test. The figure shows the p-values associated to the non overlapping multi-period variance test for the selected financial indexes over the sample period 8 February 2001–31 December 2019. Panel (a) shows the test results when considering a lag number equal to $\lceil log(T) \rceil$, whereas panel (b) illustrates the test results considering a lag number of 20. The dashed line represents the 5% significance level. Blue and red colours indicate the non-rejection and rejection of the null hypothesis at a 5% significance level, respectively.



(a) America

(b) Eastern and Northern Europe

(c) Western and Southern Europe

(d) Asia

(e) Africa and Oceania

Fig. A.3. Financial indexes return distributions. The figure shows the returns distributions, expressed in percentage terms, of the selected financial indexes over the period 8 February 2001–31 December 2019.

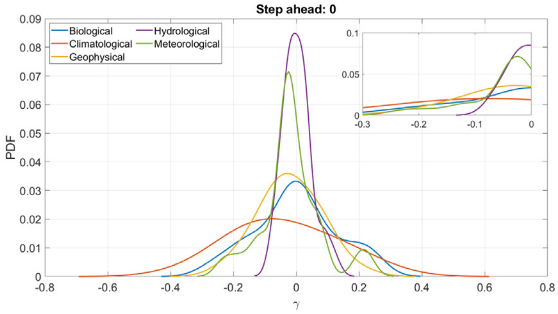
Table A.2
The topology of natural disasters.

Disaster group	Disaster main type	Disaster sub-type
Geophysical	Earthquake	Ground movement
		Tsunami
	Mass Movement (dry)	Rock fall
		Landslide
	Volcanic activity	Ash fall
		Lahar
		Pyroclastic flow
		Lava flow
Meteorological	Storm	Extra-tropical storm
		Tropical storm
		Convective Storm
	Extreme temperature	Cold wave
		Heat wave
		Severe winter conditions
	Fog	–
Hydrological	Flood	Coastal flood
		Riverine flood
		Flash flood
		Ice jam flood
	Landslide	Avalanche (snow, debris, mudflow, rockfall)
	Wave action	Rogue wave
		Seiche
Climatological	Drought	–
	Glacial Lake Outburst	–
	Wildfire	Forest Fire
		Land fire: Brush, bush,
		Pasture
Biological	Epidemic	Viral Disease
		Bacterial Disease
		Parasitic Disease
		Fungal Disease
		Prion Disease
	Insect	Grasshopper
	infestation	Locust
	Animal Accident	–

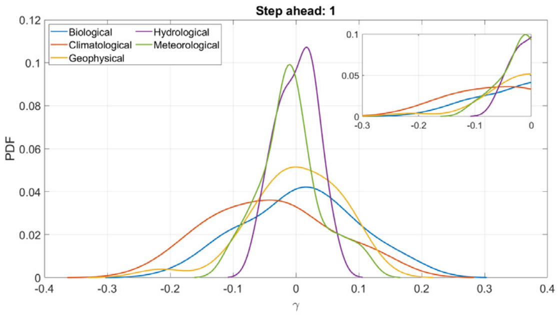
The table shows the classification of natural disasters considered into disaster groups, disaster main type and sub-type of events.

Table A.3
United States SARS-CoV-2 related events.

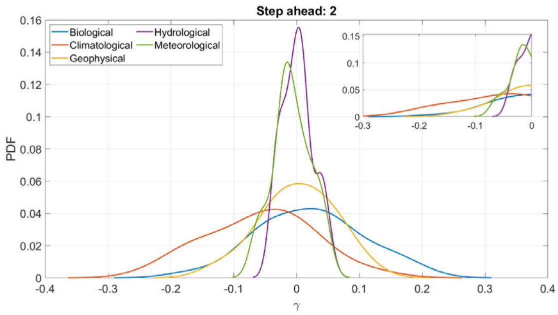
20/01/2020	First confirmed case.
29/02/2020	First reported death.
11/03/2020	The World Health Organization's Director-General declares that COVID-19 can be characterized as a pandemic.
13/03/2020	Approval of an aid economic package for workers and individuals.
16/03/2020	Trump issues guidelines to avoid 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.



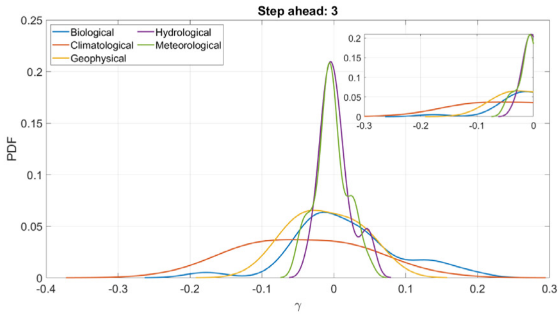
(a) $t = 0$



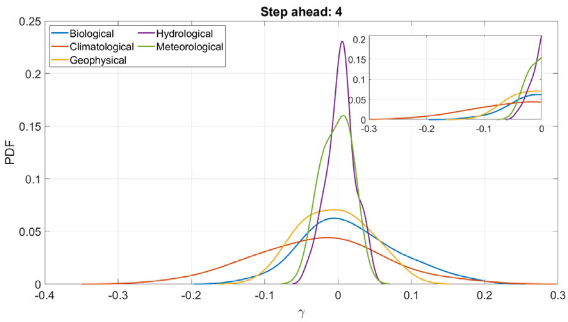
(b) $t = 1$



(c) $t = 2$



(d) $t = 3$



(e) $t = 4$

Fig. A.4. Kernel densities of the estimated $\gamma_{i,t}$ parameters. The figure shows the kernel densities of the $\gamma_{i,t}$ regression coefficients associated to the impact of each source of natural shock t periods ahead the occurrence of the event.

Table A.4
Natural disaster risk strategy Sharpe ratios.

Disaster type	Bench.	Top-10	Top-25	Top-50	Top-75	Top-90	Top/Bottom
Biological	0.045	0.065	0.017	0.015	0.032	0.047	0.016
Climatological	−0.001	0.081	0.013	−0.023	−0.008	−0.011	0.056
Geophysical	0.022	0.035	0.011	0.022	0.022	0.020	0.010
Hydrological	0.036	0.022	0.031	0.030	0.027	0.033	−0.031
Meteorological	0.031	0.034	0.031	0.034	0.029	0.033	0.027
Total	0.026	0.047	0.021	0.015	0.020	0.024	0.016

The table shows the average daily Sharpe ratios of strategies which account for the sensitivity to natural disasters of world indexes from 8 February 2014 to 31 December 2019. The table reports figures for several percentile portfolios: 10-th, 25-th, 50-th, 75-th, 90-th. Decile portfolios are redefined each in-sample window and the corresponding 500-day out of sample return time series are stacked to form a full sample period for each decile portfolio on which we calculate summary statistics. *Top/Bottom* is the portfolio obtained opening long positions in the best-performer decile indexes and short ones in those belonging to the worst-performer decile.

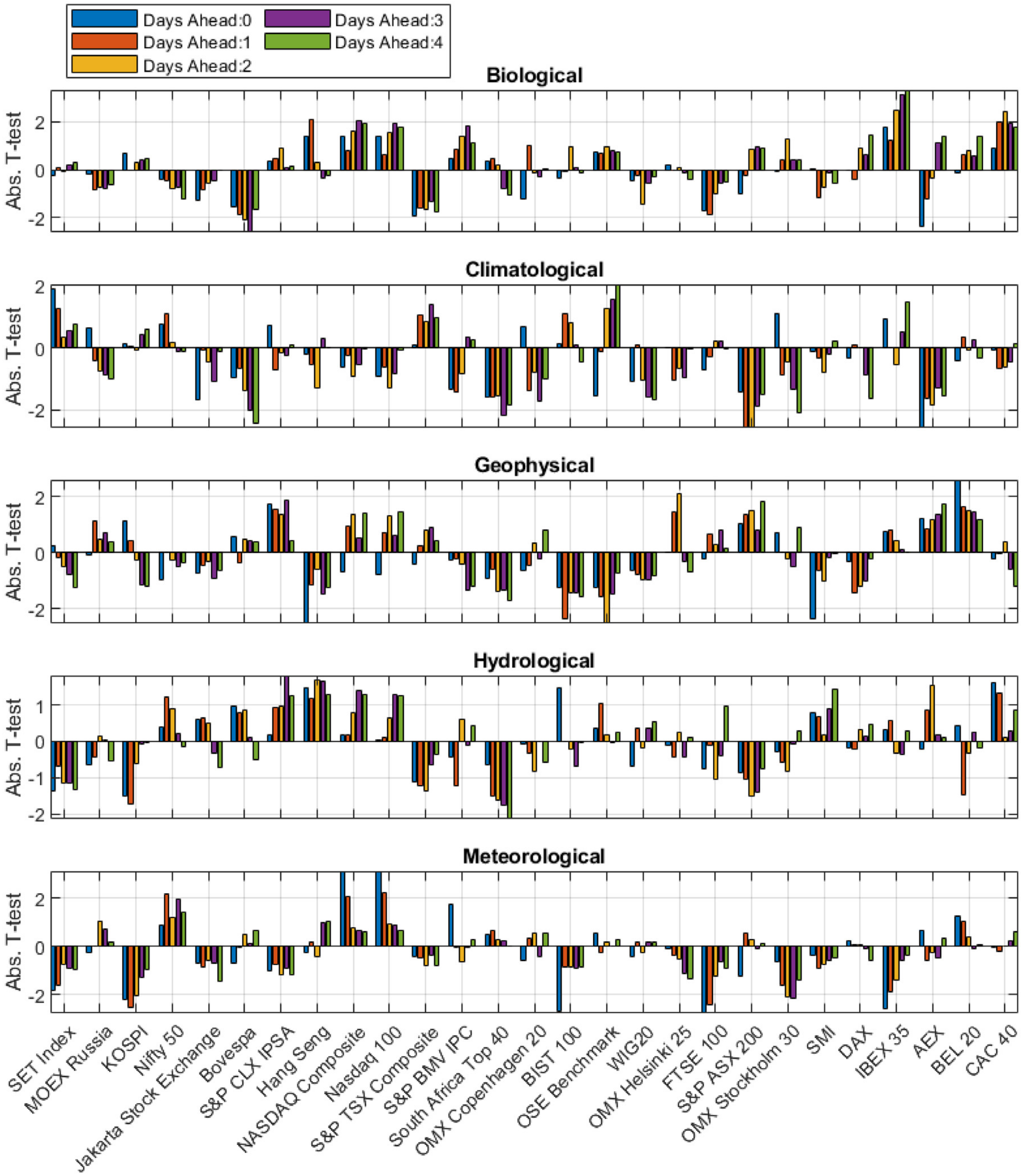


Fig. A.5. Absolute values of t-test related to the γ estimates The figure shows the absolute values of the t-test statistics associated to the γ estimates of biological, climatological, geophysical, hydrological and meteorological events for the selected stock indexes, with $t = 0, 1, 2, 3, 4$ being the step ahead the event date.

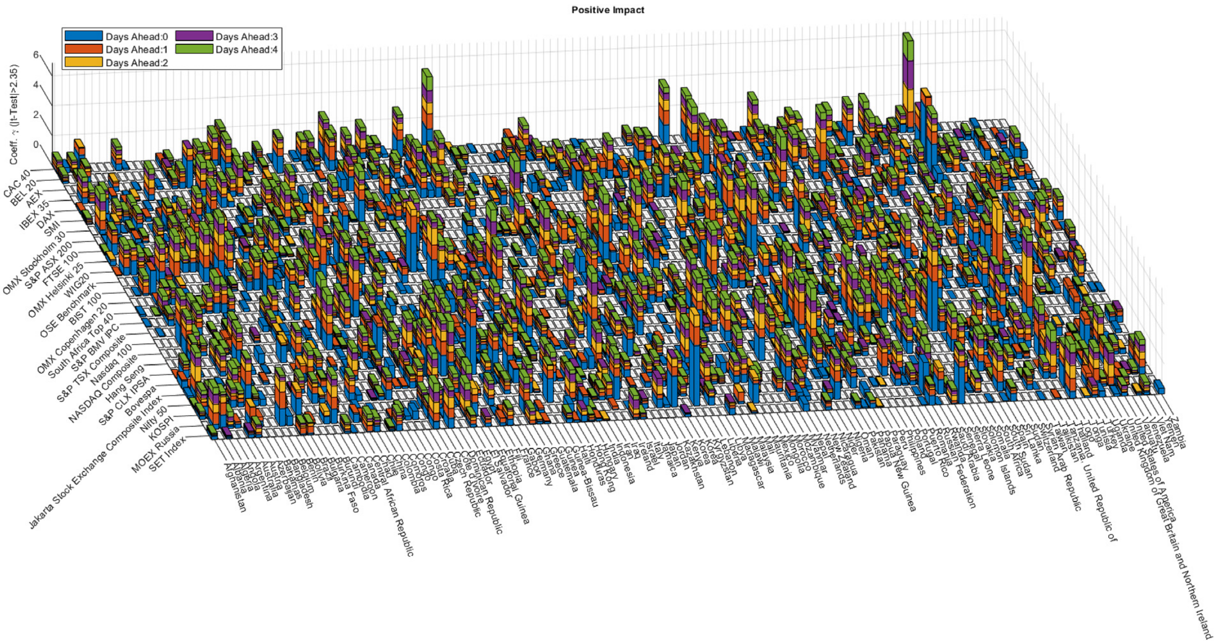


Fig. A.6. Positive AR estimates for coefficients with test statistics greater then 2.35. The figure shows the positive estimates of the $\gamma_{i,t}$ regression coefficients with t-test statistics greater then 2.35 and with $t = 0, 1, 2, 3, 4$ being the step ahead the event date. Coefficients are aggregated over different types of natural disasters.

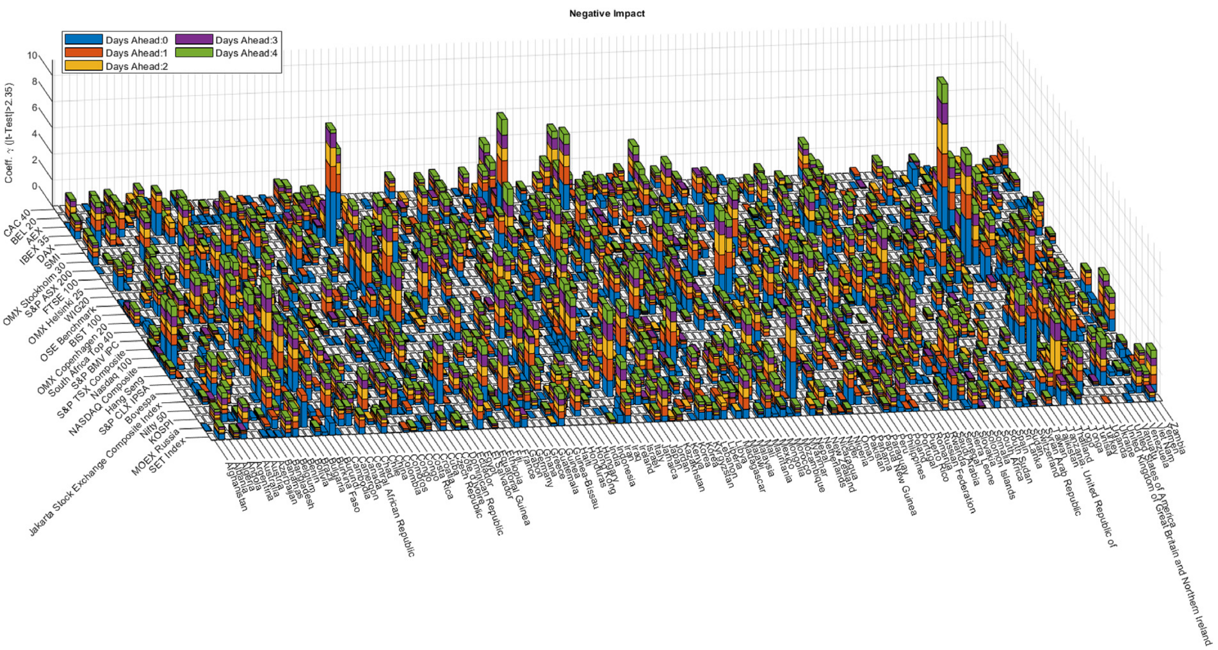
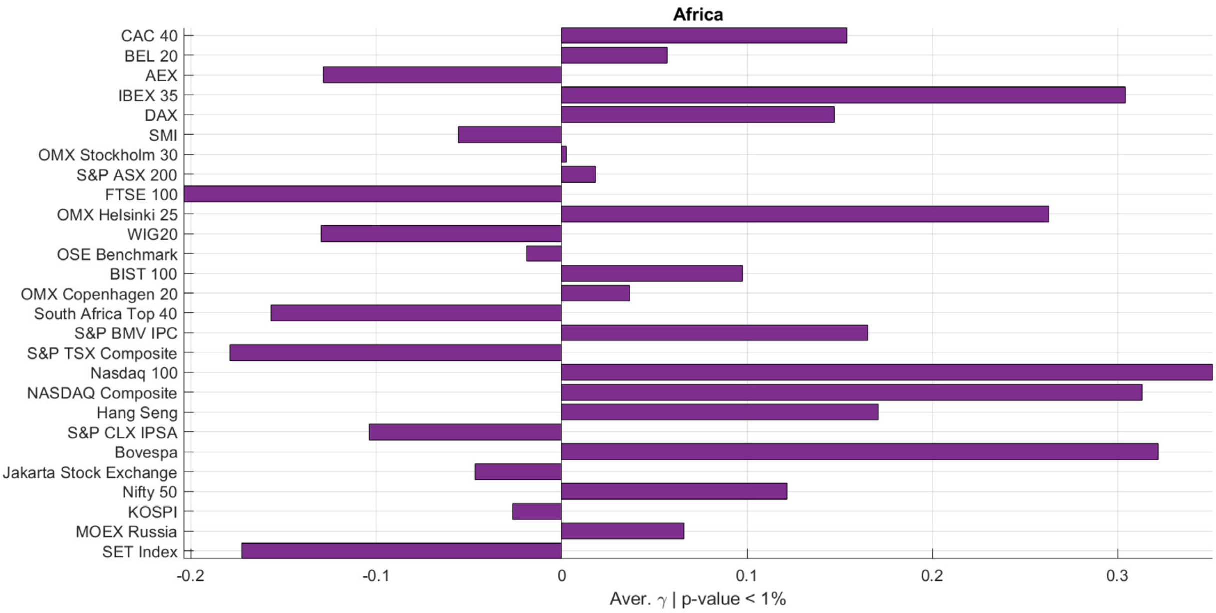


Fig. A.7. Negative AR estimates for coefficients with test statistics greater then 2.35. The figure shows the absolute value of the negative estimates of the $\gamma_{i,t}$ regression coefficients with t-test statistics greater then 2.35 and with $t = 0, 1, 2, 3, 4$ being the step ahead the event date. Coefficients are aggregated over different types of natural disasters.



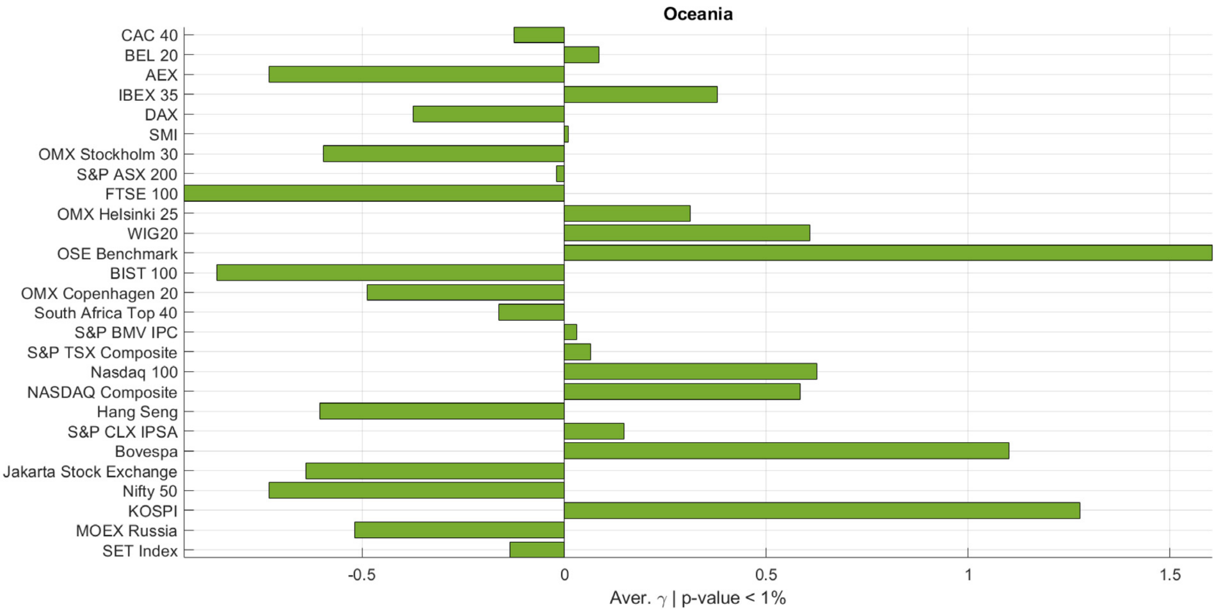


Fig. A.8. Estimated average CARs from natural disasters in Africa and Oceania. The figure shows the estimated average CARs associated to natural disasters occurring in African and Oceanian countries by market index. We consider the average of statistically significant effects, namely those coefficients reporting a *p*-value which is less than 1%.

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