# We Are All in the Same Boat: Cross-Border Spillovers of Climate Risk Through International Trade and Supply Chain*


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**Abstract**

Are assets in a landlocked country subject to sea-level rise risk? We highlight a new mechanism by which physical climate risk affects countries: the cross-border spillover effects that propagate through international trade linkages. Basing our findings on historical data between 1970 and 2018, we observe that globalization increased the similarity of countries' global physical climate risk exposures. Exposures to foreign climate disasters in major trade partner countries (both upstream and downstream) lower the home-country stock market returns for the aggregate market and for the tradable sectors. We also find that exposures to foreign long-term climate change risks reduce the asset price valuations of the tradable sectors at home. Climate adaptation efforts in a country can have positive externalities on other countries' macrofinancial performance and stability through international trade.



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# 1 Introduction

International cooperation is indispensable to mitigate the negative consequences of climate change (Paris Agreement, 2015). Global emission and temperature goals cannot be achieved without efforts by all countries. Emerging market and developing economies need financing and technology from advanced economies to transition to green production and adapt to climate disasters (Stavins et al., 2014). However, the distribution of climate risks[1] is uneven across space. Previous research argues that while many warm and poor countries may be severely hit by global warming, many cool and rich countries may not be harmed by and may even benefit from higher temperatures (Diffenbaugh and Burke, 2019). The latter group of countries may thus lack the incentive to take costly climate change mitigation actions. This view raises questions about the sustainability of international cooperation in combating climate change.

In this paper, we show that this view is partial by asking the following question: Are assets in landlocked countries subject to sea-level rise risk? We highlight a new mechanism by which climate change affects countries that may not face high climate risks themselves: the cross-border spillover effects that propagate through international trade linkages. We provide the first batch of empirical evidence that shows that a climate disaster that disrupts economic activities in any part of the global supply chain significantly affects the macrofinancial performance and stability of other countries that are connected to the network. Globalization has brought about significant economic benefits to global economies, but it has also fundamentally altered how climate-related risks are shared, allocated, and priced. Therefore, understanding the cross-border spillover effects of climate risks helps assess the implications of climate change for the macrofinancial stability of individual countries and informs collaborative climate adaptation measures because of their positive externalities through the supply chain.

The COVID-19 pandemic and associated government lockdown measures provide a recent example of how a disaster[2] in one country can disrupt global economic activities by pausing the international flows of goods, services, and people. Cerdeiro et al. (2020) finds that Chinese exports declined by 30 percent from late January to early March 2020, when China imposed a COVID-19 lockdown.[3] They also observe a second wave of global trade

[1] In this paper, we refer to "climate risk" broadly as the risk that climate disasters, such as hurricanes and floods, will occur. "Climate change" could change the magnitude, frequency, and geographic allocation of climate disasters and, hence, climate risk.

[2] A public health disaster in the case of COVID-19.

[3] They apply a new machine-learning technique to the real-time Automatic Identification System signals sent by global cargo ships.

decline starting in early April 2020, when the US and many European countries followed up by enforcing lockdown measures. Baldwin and Freeman (2020) refers to these patterns as global supply chain "contagion and reinfection". Even if a country is free from the virus or has brought the virus under control, it still suffers from the negative supply and demand shocks in the foreign countries that currently are battling the virus.

Climate disasters can have similar implications for global supply chains. Climate disasters in one country can destroy local physical and human capital and shut down roads and factories. Yet they also disrupt economic activities in other countries that rely on the disaster-hit country for imports and exports. As an example,[4] the severe floods in Thailand in 2011, which claimed hundreds of lives and affected millions, halted automobile parts production and assembly in the country. Japanese car makers that used Thailand as a key supplier in Southeast Asia had to pause their car production and sales globally. For instance, a report[5] finds that "Toyota's three plants in eastern Thailand were unaffected by the weather, but production was halted due to parts shortages." The Japanese headquarters was affected as well. Toyota claimed that it had to cut car production in Japan by a total of 6,300 vehicles due to the flood in Thailand, a sizable number given the 37,500-unit direct loss from Toyota's damaged plant in Thailand.[6] The cumulative stock returns in the automobile sector in Japan were -8.7 percent during the period of 20 days before to 40 days after the Thai flood.[7]

These examples show that globalization has connected countries and sectors and exposed their vulnerability to foreign climate-related disasters and risks. In this paper, we formally evaluate the mechanism with historical data on global climate disasters, country-sector level stock price indices, and country-bilateral international trade for 68 global economies and from 1970 to 2018. We introduce a conceptual discussion that characterizes exposures to global climate risks through international trade and we empirically investigate how asset prices reflect these exposures. The paper proceeds in four steps.

First, we construct, for each country (the home country), its upstream (the countries that sell to the home country) and downstream (the countries that buy from the home

[4] As the second example, Cerdeiro et al. (2020) finds that Hurricane Maria, which caused severe damage in Puerto Rico in 2017, reduced offloading vessel traffic in that country by as much as 75 percent, disrupting international trade. It took about 10 days for the vessel traffic to recover.

[5] See this news.

[6] See this news and this news. Toyota's Thai plants produced 630,000 vehicles in 2010. Therefore, the direct loss and the indirect loss in the Japanese headquarters from the Thai flood was about 6 percent and 1 percent, respectively, of Toyota Thai plants' total output—a non-negligible fraction. The key point made with the calculations, though, is that the indirect loss from the cross-border spillovers is considerable compared to the direct loss.

[7] In EM-DAT, the disaster date is documented as November 3, 2011. We compute the cumulative returns from October 7 to December 29. The cumulative return in the Japanese market index during the same period was -0.7 percent.

country) climate risk exposures, combining metrics of climate vulnerability (e.g., historical disaster damages, exposures to future climate change risks) and the country's trade patterns (upstream and downstream trade shares with all trade partners including the home country). With these exposure measures in hand, we construct a pair of global spillover indexes of upstream and downstream climate risks. The spillover indexes capture the extent to which globalization reduces cross-country dispersion in exposures to global climate risks. Intuitively, consider a landlocked country in the high latitudes that may have limited exposures to climate-related risks, such as sea-level rise and tropical cyclones, within its border. Opening trade with the low-latitude Pacific countries would therefore increase its global climate risk exposure. In contrast, an island country in the Pacific likely face high home-country climate risks yet opening trade with other countries may diversify away its high exposure. Consequently, as globalization deepens, all countries are coming to resemble one another over time in terms of global climate risk exposures.

Second, based on an event study approach and on historical climate disasters, we empirically investigate the stock market response in the aggregate market and individual sectors to exposures to foreign climate disaster. We focus on the response in the disaster-hit country's major exporting and importing partners. We find that through both upstream and downstream trade linkages the aggregate stock market is negatively affected by foreign climate shocks. On average, in both the upstream and downstream, the aggregate stock market index experiences a drop of 0.5 percent from 20 trading days before a foreign climate disaster to 40 trading days after it. The impact on sectoral stock returns varies across sectors and is significant for most typical tradable sectors. In the automobile sector, for instance, the negative impact in the upstream foreign country can be as high as -2 percent immediately following a climate disaster.[8]

Third, we examine whether the size of the shock, trade shares, and sector characteristics affect the degree of the cross-border spillovers of climate shocks. We find that, for the average sector, the foreign disaster magnitude and the share of trade with the disaster-hit foreign country is indeed negatively associated with the stock market response at home. However, the association differs with respect to sectors. It is negative and significant for most tradable sectors but is not significant for most non-tradable sectors. Inspired by these findings, we formally show that the tradability of sectors[9] is a key determinant for the effect of cross-border spillovers. Conditional on the exposures to foreign disasters, the

[8]Note that these estimates reflect the effect of an average climate disaster in the largest trade partner country. The total impact is greater if we only consider the large foreign climate disasters and if we add up the impact of the disaster in all trade partner countries.

[9]Defined as the ratio of the total value of imported inputs or total exports to the sector's total value-added.

sectors that are more tradable in terms of importing respond more negatively to upstream disasters, and the sectors that are more tradable in terms of exporting respond more negatively to downstream disasters. These results further confirm that the spillover channel is through trade linkages. Because the financial sector is often exposed to risks in all sectors, we also examine the effects of foreign climate shocks on financial sector stock prices and the role of institutional factors. We find that a higher degree of international trade guarantees for domestic firms and a higher total capital to risk-weighted assets ratio are associated with a lower impact from climate risk spillovers.

Fourth, the paper examines whether exposures to foreign long-term climate change risks through international trade are reflected in countries' sectoral stock market valuations. Higher exposures to trading partners that have high climate risks (for example, a higher expected frequency of climate disasters) imply greater risk to operating cashflows and profitability of the sector. As a result, the stock market valuation of the sector is likely be lower than it would be under less foreign risk exposure. We empirically investigate this relationship by linking standard valuation metrics, such as price-to-earnings ratio (P/E ratio) at the sector level, to exposures of foreign climate change risk. We find that higher foreign climate change risk exposures are indeed associated with lower P/E ratios. The relationship is particularly strong for tradable sectors. We separate the effects of getting more exposed to the high climate risk foreign countries from the effects of openness to trade with all foreign countries. We show that these results are not naively driven by openness to trade or trading with wealthier countries.

We identify international trade as an important channel for the propagation of climate shocks by conducting placebo tests on non-major trading partners and by distinguishing tradable sectors from other sectors. The results we have found may not be driven by other potential channels, such as financial spillovers through global capital flows and the spread of natural disasters based on geographical proximity, among others, because these alternative channels do not have asymmetric effects either between major trade partners and other countries or between tradable sectors and other sectors.

This paper assumes that in the short run the global trade partnership and network are resilient to climate disasters.[10] This assumption is reasonable given that in recent decades globalization has been the process (driven, for example, by better technologies

[10]This assumption makes two allowances: that a downstream country may import less from the upstream foreign countries hit by a climate disaster or negatively impacted by climate change risks; and that an upstream country may export less to the downstream foreign countries hit by a climate disaster or negatively impacted by climate change risks. In fact, the assumption is based on the gravity model of international trade. The assumption rules out two possibilities: that a country can deliberately decouples from a foreign country which it believes has higher climate risks or that it can adjust trade in ways that drastically depart from the predictions of the gravity model (with more details in Section 2).

of international trade, lower global tariffs, the opening up of China, the end of the Cold War, and so on) most exogenous to considerations of climate change risks (more details about this assumption appear in Section 2). Admittedly, climate disasters and climate risks, if they are sufficiently severe, can drastically affect international trade networks in the long run. For example, a country might deliberately decouple from climate risks by concentrating their supply chains on countries that have a comparably limited exposure to climate change.[11] Instead, this paper contributes to the literature by providing a partial equilibrium view of how climate risks propagate in the cross section of countries through a fixed global trade network.

This paper contributes to the important policy discussions about climate change adaptation. It suggests that optimal adaptation efforts require collective action in a multilateral framework. Given the cross-country spillovers documented in this paper, helping other countries, especially trade partners, to build resilience against climate shocks also enhances the home country's climate resilience. The paper contributes to the ongoing analytical work agenda of central banks and financial regulators (such as the Network of Central Banks and Supervisors for Greening the Financial System, or NGFS) that investigates the relationship between climate change and financial stability. While this paper focuses on physical climate risks, the conceptual framework and analytical method are applicable to examinations of transition risks related to climate change (the risks that countries and sectors may encounter during the transition to a greener economy).

Our paper contributes to the literature in several important ways. First, it contributes to the literature on the economic consequences of climate change. We only present a brief survey of this literature.[12] Using panel data from 1970 to 2006 for Caribbean countries, Hsiang (2010) finds that climate disasters, such as cyclones, lower GDP, and the effect is heterogeneous across sectors. Dell et al. (2012), Burke et al. (2015) and Kahn et al. (2019) find that high temperatures have negative effects on economic growth, especially for low-income countries. Somanathan et al. (2015) finds similar effects using Indian firm level data. On the financial market implications of climate change, Hong et al. (2019) finds that a country's drought indexes can predict the country's food sector stock returns. Addoum et al. (2019) observes that extreme temperatures significantly impact earnings and stock prices in more than 40 percent of industries. Notably, Chapter 5 of the IMF Global Financial Stability Report (International Monetary Fund 2020, henceforth the GFSR) employs an event study approach and finds that a climate disaster lowers the stock market valuation of domestic aggregate market, banking, and insurance sectors by about 1-2 percent on average. We contribute to this literature by demonstrating that climate change sig-

[11] If this is the case, we may exaggerate the negative impact of foreign climate risks.

[12] For a more detailed survey, see Botzen et al. (2019).

nificantly affects economic performances of the importing and exporting partners of the countries that are directly affected.

The paper contributes to the international economics literature on the propagation of shocks across regions and sectors and business cycle synchronization. For example, Di Giovanni et al. (2018) finds that the performance of a firm correlates with business cycle level fluctuations in countries where the firm have established international trade and multinational production relations. Different from them, we document empirical evidence of business cycle synchronization on the aggregate, country-sector level. Another line of this literature is more quantitative. For example, earlier works like Backus et al. (1992) and recent works like Caliendo et al. (2017), among others, use quantitative trade and macroeconomic models to show that economic shocks that hit one region or sector could propagate to other parts of the economy and could have aggregate implications. We lend empirical support to the models that have been used in this literature.

A nascent literature has studied the propagation of climate risks through trade and production linkages. The paper most related to our work is Barrot and Sauvagnat (2016) which uses a US firm-level database and finds that natural disasters that hit specific input suppliers reduce the sales growth and stock prices of their customers. We focus on the cross-border spillovers with international trade, a linkage that has often been ignored by climate scientists and economists. Other related works include Boehm et al. (2019) which finds that the 2011 Tōhoku Earthquake harmed business performance of Japanese foreign affiliates abroad because it disrupted the critical headquarters input supplies to subsidiaries. Carvalho et al. (2016) also examines the 2011 Tōhoku Earthquake, but they focus on the supply chain disruptions within Japan. Yet we find that climate disasters have substantial aggregate implications for the hit-country's main trade partner countries and undermine their macrofinancial stability. Dingel et al. (2019) finds that climate change increases the global spatial correlation of productivity shocks and increases the cross-country welfare dispersion, whereas we focus on climate shocks' implications on the first order moments of economic outcomes. A few recent works, for example, Cruz et al. (2020) and Conte et al. (2020), use quantitative trade models to study the macroeconomic consequences of climate change, whereas we develop a new empirical strategy that credibly identifies the cross-border spillovers of climate shocks, which is a key mechanism assumed by these models but has yet to be tested.

The rest of the paper is organized as follows. Section 2 describes our data and variable construction. Section 3 constructs new measures of countries' exposures to global climate shocks and climate shock spillover indices that gauge how similar countries are in terms of climate shock exposures. Section 4 studies the response in stock market returns to foreign climate disasters with an event study approach. Section 5 inquires factors that affect the magnitude of the response. Section 6 investigates the relationship between stock market valuation and exposures to foreign long-term climate change risks. Section 7 concludes.

## 2 Data and variable construction

We assemble a comprehensive data set for climate disasters, bilateral trade dynamics, and sectoral stock valuation and returns in a sample of 68 countries between 1970 and 2018.[13] Among these countries, 34 are advanced economies, and the other 34 are emerging markets and developing economies. We study the same set of countries as in the GFSR. Therefore, we ensure comparability between the results in the two publications. Table A.1 lists these countries.

We introduce two sets of key international trade shares that guide our analysis throughout the paper. Define country $n$'s expenditure share on country $i$ in year $y$, $\pi_{ni,y}$, as the ratio of trade flow values from $i$ to $n$, divided by the total expenditure on final (consumption and investment) and intermediate goods by country $n$, $X_{n,y}$:

$$\pi_{ni,y} = \frac{x_{ni,y}}{X_{n,y}}$$

Given a buying country $n$, the sum of its expenditure shares on all selling countries equals 1: $\sum_{i=1}^{N} \pi_{ni,y} = 1$. Define country $i$'s output share to country $n$, $S_{ni,y}$, as the ratio of the trade flow values from $i$ to $n$, divided by the gross output of country $i$, $Y_{i,y}$:

$$S_{ni,y} = \frac{x_{ni,y}}{Y_{i,y}}$$

Given a selling country $i$, the sum of its output shares to all buying countries equals 1: $\sum_{n=1}^{N} S_{ni,y} = 1$.

We obtain information on country-bilateral total trade for all countries and years from the United Nations Comtrade Database.[14] We acquire countries' annual GDP data, $VA_{i,y}$, from the United Nations National Account Database. We get the value added to gross

[13] Although the climate disaster and stock price data used by the GFSR cover the years 1970–2019, the international trade data from UN Comtrade are only available until 2018. As a result, our sample ends in 2018, one year earlier than the GFSR's.

[14] UN Comtrade sources raw data from national customs and covers only trade in goods (most service trade does not pass through customs). Therefore, we assume that the expenditure and output shares of goods trade represent the respective shares of total trade. We believe this is a reasonable assumption given that service trade accounted for only about 22 percent of world total trade as of 2018 (see this webpage).

output ratio ($VAS_{i,y}$) from the international input-output database constructed by Johnson and Noguera (2017) and the OECD Analytical Activity of Multinational Enterprises database (henceforth OECD AAMNE, see Cadestin et al. 2018). With these variables we compute the expenditure shares, $\pi_{ni,y}$, and the output shares, $S_{ni,y}$. We discuss the detailed procedures in Appendix Section A.1.

Figure B.1 plots the world trade-to-world GDP ratio overtime. This is a commonly used measure of globalization in international trade (Eaton et al., 2016). The ratio was as low as about 0.07 in 1970, but it rose sharply in the 1970s, flattened in the 1980s, and returned to a strong upward trajectory in the 1990s and in the first half of the 2000s. The trend was clearly broken by the 2007-2009 Great Recession, when the world trade-to-world GDP ratio fell by about 20 percent. International trade economists call this phenomenon the "Great Trade Collapse". The ratio bounced back after the Great Recession, but it never reached its pre-recession peak of about 0.25. After the recovery, it started to drop again. As of 2018, the world trade-to-world GDP ratio was about 0.20.[15]

Throughout this paper we maintain the following key assumptions on the trade shares. We assume country $n$'s expenditure share on country $i$, $\pi_{ni,y}$, are not affected by the climate disasters that occur in the downstream country $n$ in year $y$.[16] We also assume country $n$'s share in country $i$'s gross output, $S_{ni,y}$, conversely, are not affected by the climate disasters that occur in the upstream country $i$ in year $y$.[17] These assumptions are supported by the international trade literature on the short-run stickiness of supply chains (for example, Antras et al. 2017). They are also supported by the gravity equation literature on international trade. Researchers conclude, based on their estimated parameters of expenditure shares, that such shares increase in the size of the upstream economy and decrease in the bilateral distance, but they are not significantly affected by the size of the downstream economy. Correspondingly, the output shares increase in the size of the downstream economy and decrease in the bilateral distance, but are not significantly affected by the size of the upstream economy.[18] Therefore, an upstream disaster that

[15]It is unclear whether the post-recession dynamic was a short-run, business-cycle pattern or the kick-off of a new, reversed trend.

[16]This assumption allows for $\pi_{ni,y}$ to be affected by disasters to upstream country $i$. If a disaster reduces the supplies from an upstream country, the downstream country will spend a smaller share on that country and larger shares on all other countries (including itself). This assumption rules out the possibility that an upstream foreign country $i$ stop selling anything to, or decouple from, $n$ within one year after $n$ is hit by a disaster. In this case the disaster that hit $n$ would lead to $\pi_{ni,y} \to 0$, which violates the assumption.

[17]This assumption allow for $S_{ni,y}$ to be affected by disasters to downstream country $n$. If a disaster reduces the expenditure from a downstream country, the upstream country will sell a smaller share to that country and larger shares to all other countries (including itself). This assumption rules out the possibility that a downstream foreign country $n$ stop buying, or decouple, from $i$ within one year after $i$ is hit by a disaster. In this case the disaster that hit $i$ would lead to $S_{ni,y} \to 0, \forall n \neq i$, which violates the assumption.

[18]The gravity equation literature, starting with Tinbergen (1962), has found that country-bilateral trade

reduces the GDP in country $i$ decreases downstream countries' expenditure shares on country $i$ ($\pi_{ni,y}$), but does not significantly affect $i$'s output shares to downstream countries ($S_{ni,y}$). Correspondingly, a downstream disaster that reduces the GDP in country $n$ decreases upstream countries' output shares to country $n$ ($S_{ni,y}$), but does not significantly affect $n$'s expenditure shares on upstream countries ($\pi_{ni,y}$). These assumptions imply that an upstream climate disaster reduces the upstream country's supplies to downstream countries proportionally, according to the annual output shares of the upstream country. Similarly, a downstream climate disaster reduces the downstream country's purchase from upstream countries proportionally, according to the annual expenditure shares of the downstream country.

The climate disaster data is acquired from the same data source as the GFSR: the Emergency Events Database (EM-DAT).[19] In the database, the disaster damages are measured in three ways: total number of deaths; total number of people affected; and total monetary loss. We use $Damage_{i(d)}$ to denote the disaster damage in country $i$ that is caused by disaster $d$. We use $Damage_{i,y}$ to denote the total climate disaster damage in country $i$, year $y$. Among all the climate disasters, Hurricane Katrina of 2005 caused the largest monetary damage to the host country in constant dollar terms ($125 billion). The 2011 Thai floods caused the largest monetary damage relative to the host country's GDP (10.1 percent). Other disasters are less drastic in magnitudes. The average disaster causes $783 million monetary damage in current USD and 113 deaths, and it affects 1.36 million people. On average, the monetary damage is 0.01 percent of the hit country's GDP (see Table A.4 for the percentiles of the disaster damages).

To measure climate change risks, we rely on the Climate Change Exposure Index from Verisk Maplecroft as our main data source. The index characterizes the degree to which countries are exposed to the physical impacts of future climate disasters and cli-

flows are characterized with $Trade_{ni} \propto \frac{GDP_n^{\alpha} GDP_i^{\beta}}{Distance_{ni}^{\zeta}}$, where $\alpha, \beta, \gamma \approx 1$. Therefore, approximately, $\pi_{ni} = \frac{Trade_{ni}}{GDP_n} = \frac{GDP_i}{Distance_{ni}}$, which is not significantly affected by downstream GDP, $GDP_n$, and $S_{ni} = \frac{Trade_{ni}}{GDP_i} = \frac{GDP_n}{Disntance_{ni}}$, which is not significantly affected by upstream GDP, $GDP_i$. Chaney (2018) provides a microfoundation for the findings. As a result, the assumptions rule out the possibility that within one year after a climate disaster hit a country, other countries adjust their trade shares in a way that is significantly different from the predictions by the gravity equation, for example, to immediately stop exporting and importing with the country that is hit by the disaster.

[19]In EM-DAT we keep the following types of climate disasters: floods; storms (hurricanes); droughts; wildfires; and extreme temperatures, and drop the other disasters that are not related to climate. For a climate event to be considered a disaster, it must satisfy at least one of the following criteria: (1) 10 or more deaths; (2) 100 or more people affected; or (3) the declaration of a state of emergency and/or a call for international assistance. Following the GFSR and excluding tiny disasters, we further restrict the sample to those that had a rate of affected population greater than 0.5 percent or damage greater than 0.05 percent of GDP. To obtain a meaningful identification for our event study, we restrict our sample to the climate disasters that have an exact start date.

mate changes.[20] Climate change risks, which generally refer to a long-term view, measure the likelihood of climate disasters will occur in the future. Therefore, we fix a country's climate risk to its value in 2018.[21] We denote the climate change hazard index with $R_i$.[22]

To study the equity market response, we consider the following stock market variables: stock index returns, price-to-earnings ratios, and earnings per share. We obtain country-sector level, country-aggregate level, and global sector level information for these variables from Refinitiv Datastream. From the same data source, we also acquire three-month government bond yield data for the sample economies. We refer to the country whose stock market is affected by foreign climate shocks as the home country. The countries that sell to the home country are the upstream countries. Climate shocks that affect the upstream countries are referred to as the upstream shocks. The countries that buy from the home country are the downstream countries. Climate shocks that affect the downstream countries are referred to as the downstream shocks.

To confirm that international trade is the key propagation channel, we show that the tradable sectors in the home country respond more to foreign climate shocks. The sector level stock indexes from Datastream cover 26 sectors (Table A.2). However, Datastream does not provide information about the tradability of these sectors. We use the World Input-Output Database (WIOD) 2016 release (Timmer et al., 2015) to compute sector tradability. To the best of our knowledge, this international input-output database has the most granular sector classifications (a total of 56 sectors; Table A.3). It allows matching with the sector level stock indexes on a more disaggregated level. The WIOD 2016 release covers 2000–2016. We use 2000 as the benchmark year to approximate the sector tradability for all years in the sample.

We consider both exporting and importing tradability. A sector that is more tradable in terms of exporting should respond more to downstream climate shocks. Similarly, a sector that is more tradable in terms of importing should respond more to upstream climate shocks. Denote world total value added of sector $s$ with $VA^s$ and world total

[20]The raw data use 0 to denote the highest risk and 10 to denote the lowest risk. Following the GFSR, we construct a climate change hazard index by subtracting the raw index from 10. We then normalize the measure such that it has a mean of 0 and a standard deviation of 1. An increase in the climate change hazard index is associated with higher climate risks.

[21]The Verisk Maplecroft data is only available from 2013 to 2019. Consequently, an annual measure of country-level climate risks starting in the 1970s is unfeasible. In the years for which Verisk Maplecroft data are available, there are limited year-on-year changes in countries' climate risks.

[22]We also consider other measures of climate risks as robustness tests, including the future heat stress risk, which measures the likelihood of extreme heat; sea-level rise risk, which measures the physical threat of inundation of coastal areas due to the projected sea-level rise; an adaptive capacity index, which measures a country's ability to adjust to the possible consequences of climate change; and a climate change sensitivity index, which measures the susceptibility to future climate disasters and projected climate change. All these risk measures come from Verisk Maplecroft.

export of sector $s$ output with $EX^s$. Then the exporting tradability is constructed with:

$$TDEX^s = \frac{EX^s}{VA^s}$$

This is a sector level measure and could be considered an average across all countries. We use the ratio of world total export-to-world GDP as a measure of exporting tradability for the entire market:

$$TDEX^{mkt} = \frac{EX^{world}}{VA^{world}}$$

We construct importing tradability with the ratio of the sector's world total import in intermediate input used in the production of the sector's output, $IIM^s$, with respect to the sector's world total value added, $VA^s$:

$$TDIM^s = \frac{IIM^s}{VA^s}$$

$IIM^s$ includes the imported input from all sectors that is used in the production of sector $s$ output.[23] As a result, $TDIM^s$ constitutes an important component of a sector's total exposure to upstream foreign shocks.[24]

The importing tradability is also measured on the sector level and could be considered an average across all countries. We use the ratio of world total imports in intermediate input-to-world GDP as a measure of average importing tradability for all sectors:

$$TDIM^{mkt} = \frac{IIM^{world}}{VA^{world}}$$

The total factoring volume-to-GDP ratio and the bank regulatory capital-to-risk-weighted assets ratio are important institutional variables that can be used to explain cross-country heterogeneity in the home-country financial sector's response to foreign climate disasters (more details appear in Section 5.2). The country-year-level information for the two variables comes from the World Bank Global Financial Development Database. We report the summary statistics of the key variables used in this paper in Table A.4.[25]

[23]This includes sector s itself when it is used in the production of sector $s$ output.

[24]We consider both importing and exporting tradability because the two measures do not necessarily equal to each other. The output of some sectors–for example–construction may not be especially tradable. However, in the case of construction, their input may be tradable, and countries may import highly valued sand and stones from abroad. Therefore, these sectors, too, might be subject to foreign upstream climate shocks.

[25]To be conservative and to reduce the impact of outliers on the results, we winsorized all variables at the top and bottom 1 percent.

# 3 A cross-border climate shock spillover index

## 3.1 Exposures to global climate shocks

We refer to country $n$'s upstream exposure to global climate disasters as how much the home country is exposed to its upstream countries according to the upstream countries' output shares. The upstream exposure in year $y$ equals the weighted sum of the damages due to climate disasters, $Damage_{i,y}$, for any country $i$ in the world selling to $n$, where the weight equals the output share of the selling country $i$ to $n$, $S_{ni,y}$ (for exposures to global climate risks, replace $Damage_{i,y}$ with the country's climate change hazard index, $R_i$):

$$U_{n,y} = \sum_{i=1}^{N} S_{ni,y}\ Damage_{i,y}$$

We assume the disaster randomly destroys the output in country $i$. The loss in output then spills over to and is split among the hit country $i$'s downstream countries (including the hit-country itself) in accordance with country $i$'s output shares, $S_{ni,y}$. The loss in sales from $i$ to $n$ is therefore measured with $S_{ni,y}Damage_{i,y}$. Country $n$'s total upstream exposure adds up to the losses in sales from all countries that sell to $n$. Because the home country $n$ is also included in the summation, the upstream exposure measure captures all climate-disaster-related disruptions to both domestic and foreign suppliers.

We refer to country $i$'s downstream exposure to global climate disasters as how the home country is exposed to its downstream countries in accordance with the downstream countries' expenditure shares. The downstream exposure in year $y$ equals the weighted sum of climate disaster damages to all countries that buy from $i$, where the weight equals the expenditure share of the buying country on $i$, $\pi_{ni,y}$:

$$D_{i,y} = \sum_{n=1}^{N} \pi_{ni,y}\ Damage_{n,y}$$

In the context where the downstream country $n$ is hit by climate disasters, $Damage_{n,y}$ measures the losses in its income or total expenditure. We assume the disaster randomly destroys purchasing power in country $n$. The loss then spills over to and is split among the hit country's upstream countries (including the hit country itself) in accordance with the expenditure shares, $\pi_{ni,y}$. As a result, the reduction in purchase from $i$ by $n$ could be measured with $\pi_{ni,y}\ Damage_{n,y}$. $i$'s total downstream exposure aggregates the reductions in purchase by all countries that are in $i$'s downstream. To capture all climate-disaster related disruptions to both the home country's domestic and foreign customers it includes the home country.

A nice property of our upstream and downstream exposure measures is that those of all countries add up to the total disaster damage in the world. Therefore, our constructed measures imply that international trade changes the disaster incidences allocated between countries, whereas it does not affect the world total damage caused by the disasters:

$$\sum_{n=1}^{N} U_{n,y} = \sum_{i=1}^{N} D_{i,y} = \sum_{n=1}^{N} Damage_{n,y}$$

Two knife-edge cases help us understand the exposure measures. In the first case, international trade is shut down and countries only buy from and sell to themselves (autarky). The upstream and downstream exposures would both reduce to the home-country disaster damage: $U_{n,y} = D_{n,y} = Damage_{n,y}$. In the second case, countries spend the same share of their income on and sell the same share of their output to all countries in the world. This implies countries all trade the same way and perfectly share climate disasters. All countries would have the same upstream and downstream exposures to global climate shocks: $U_{n,y} = D_{n,y} = \frac{1}{N}\sum_{i=1}^{N} Damage_{i,y}, \forall n$. Generally, countries should have both a home-country disaster component and a component related to spillovers from foreign countries and should differ in terms of their exposures to global climate disasters.

Like the upstream and downstream exposures to global climate disasters, we can construct the upstream and downstream exposures to global climate change risks by replacing the damage variables with the measures for risks. The exposure measures help us understand how globalization affects countries' exposures to global climate disasters and climate risks. Our first application finds that as globalization deepens, countries with low home-country climate risks have increased their global climate risk exposures, while countries with high home-country climate risks have decreased their global climate risk exposures.

We illustrate the point with the examples of two (groups of) countries. Country $A$ is a representative land-locked European country (or a group of countries) in a high latitude and has low exposures to many sources of climate risks (such as tropical cyclones) in the home country. In a hypothetical world with no international trade, country $A$ would trade only with itself and had low exposure to global climate risks. Now, country $A$ trades extensively with foreign customers and suppliers. Most foreign countries that country $A$ buys from and sells to are likely to be exposed to relatively higher climate risks than country $A$. Country $A$ should now face higher global climate risks because of its linkages with foreign customers and suppliers. As these risks are realized, country $A$ is also hit with more climate disasters in the upstream and downstream along the global value chain. Thus, it is predicted that globalization increases country $A$'s exposure to global climate risks and disasters.

Country $B$ is a representative tropical coastline country (or a group of countries) in Asia Pacific and so is subject to higher home-country climate risks than an average foreign country. As country $B$ opens to trade, most countries it trades with are likely to be exposed to lower climate risks. In country $B$ this should lead to a decline in global climate risks and disaster exposures achieved through globalization.

Applying the concept to the data, we let country $A$ refer to the group of countries that are the bottom 10 percent of all countries in terms of average annual deaths from home-country climate disasters or in terms of the home-country climate change hazard index. Alternatively, we call country $A$ the low home-country shock group. Correspondingly, we let country $B$ refer to the group of countries that are among the top 10 percent of all countries in terms of average annual deaths from home-country disasters or the home-country climate change hazard index. We call country $B$ the high home-country shock group.

To confirm the hypothesis, we plot the trend in the upstream and downstream exposures for the two groups of countries. But prior to that, we note that home-country climate shocks may change differently in individual countries. Even if there are no variations in the trade shares this will lead to changes in the global exposure measures. To address this confounding factor, we first allow the year of the trade shares to be different from the year of the climate shocks. We define the upstream and downstream exposures in terms of the current global climate shocks, but the expenditure and output shares are fixed at benchmark year $y_0$:[26]

$$U_{n,y_0,y} = \sum_{i=1}^{N} S_{ni,y_0} Damage_{i,y}$$

$$D_{i,y_0,y} = \sum_{n=1}^{N} \pi_{ni,y_0} Damage_{n,y}$$

For country groups $A$ and $B$ we consider the ratio of the exposure measures with current and benchmark shares. This removes the contribution by spatial distribution of home-country climate shocks across countries to the changes in exposure measures. We call

[26] We set $y_0 = 1971$.

them the relative exposure measures:

$$Rel\_U_{A,y_0,y} = \frac{\sum_{n \in A} U_{n,y,y}}{\sum_{n \in A} U_{n,y_0,y}}$$

$$Rel\_D_{B,y_0,y} = \frac{\sum_{i \in B} D_{i,y,y}}{\sum_{i \in B} D_{i,y_0,y}}$$

The measures equal 1 in the benchmark year ($y = y_0$). If only changes in the climate shocks affected individual countries, but if there were no changes in the trade shares over time, the ratios would remain at 1.

The results are shown in Figure 1. From the 1970s through the 2000s, the low home-country shock group (country $A$) experienced an increase in the global exposures to climate disasters and climate risks. Coevally, upstream (downstream) exposure to total climate disaster-related deaths increased by about 25 (35) times . The increase in risk exposures was more moderate: the upstream (downstream) exposure to climate risks increased by about 8 percent (4 percent). On both accounts, the global exposures of the low home-country shock group (country $A$) started to fall at approximately the same time as the Great Recession .

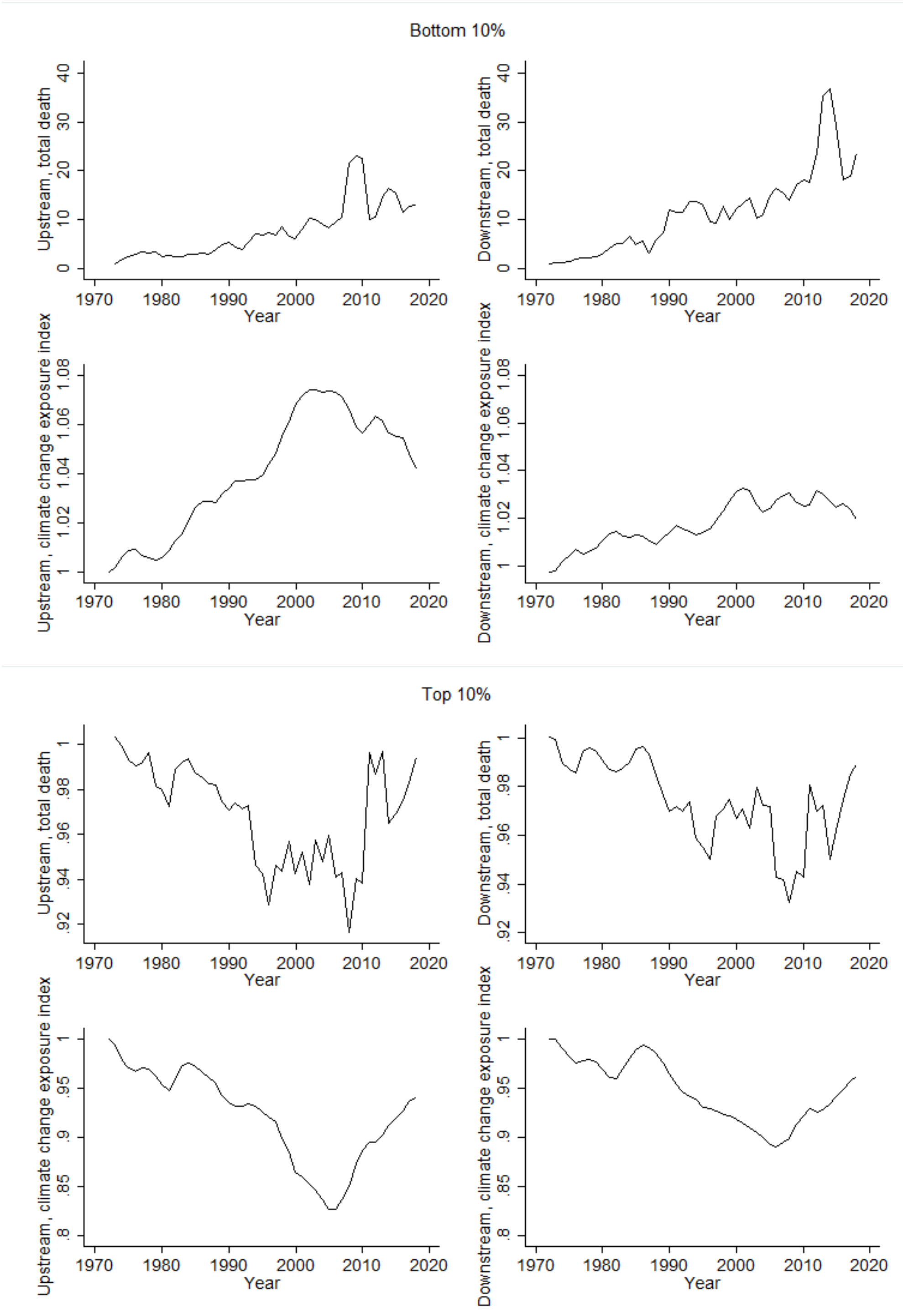
Meanwhile, the average country of the high home-country shock group (country $B$) experienced a decline in exposures to climate disasters and climate shocks from the 1970s through the 2000s. The upstream (downstream) exposure to global climate disasters dropped by about 8 percent (6 percent). The upstream (downstream) exposure to global climate risks dropped by about 20 percent (10 percent). After the Great Recession, high home-country shock countries (country $B$) began to increase their exposures.

These results show that our methodology is useful for illustrating the evolution of climate risk distribution across countries; thus, it has policy relevance. International trade patterns can have a significant impact on the global distribution of climate risk. Countries that used to have low climate risk exposures are no longer immune to extreme climate shocks because of their increasing trade linkages with countries that have higher climate risk exposures.

## 3.2 The global spillover index of climate shock exposures

The results in the previous section imply that, during the study period, the cross-country dispersion of upstream and downstream exposures of global climate risks should have

Figure 1: Exposures to global climate shocks for low and high home-country shock groups




The figures plot the upstream and downstream global climate disaster and risk exposures for the bottom and top 10 percent of the countries that have the lowest and highest annual average home-country disaster damages and climate risks. Disasters are measured with total deaths. Climate risks are measured with the climate change hazard index. Three-year moving average of the variables is plotted.

decreased with globalization. In this section, we study the dynamics of the cross-country dispersion in climate shocks by formally introducing a global spillover index of climate shock exposures. The index is defined as the ratio of the cross-country standard deviation of upstream/downstream exposures measured in benchmark year trade shares, with respect to the cross-country standard deviation of upstream/downstream exposures measured in current expenditure shares:

$$Spillover\_up_{y_0,y} = \frac{sd_n\left(U_{n,y_0,y}\right)}{sd_n\left(U_{n,y,y}\right)}$$

$$Spillover\_down_{y_0,y} = \frac{sd_i\left(D_{i,y_0,y}\right)}{sd_i\left(D_{i,y,y}\right)}$$

In the benchmark year with $y = y_0$, the global spillover indexes of both upstream and downstream exposures equal 1. As countries increasingly open to trade, the countries that have high climate risks are increasingly exposed to trading partners that have relatively low climate risks, whereas the countries with low climate risks are increasingly exposed to trading partners that have relative high climate risks. One would expect that the cross-country dispersion in the exposures would decline and the spillover indexes would rise.[27] Like the exposures to global climate shocks for individual countries, the cross-country dispersion in climate exposures is not only driven by opening to trade, but also is confounded by the rise and fall of cross-country variations in the climate shocks associated with individual countries. To eliminate this confounding component, we have in the numerator the cross-country standard deviation in climate shock exposures with current levels of climate shocks but with benchmark trade shares. If no changes occur in the trade shares over time, the spillover indexes will remain at 1. In the extreme case in which countries perfectly share climate shocks, the spillover indexes will rise to infinity.

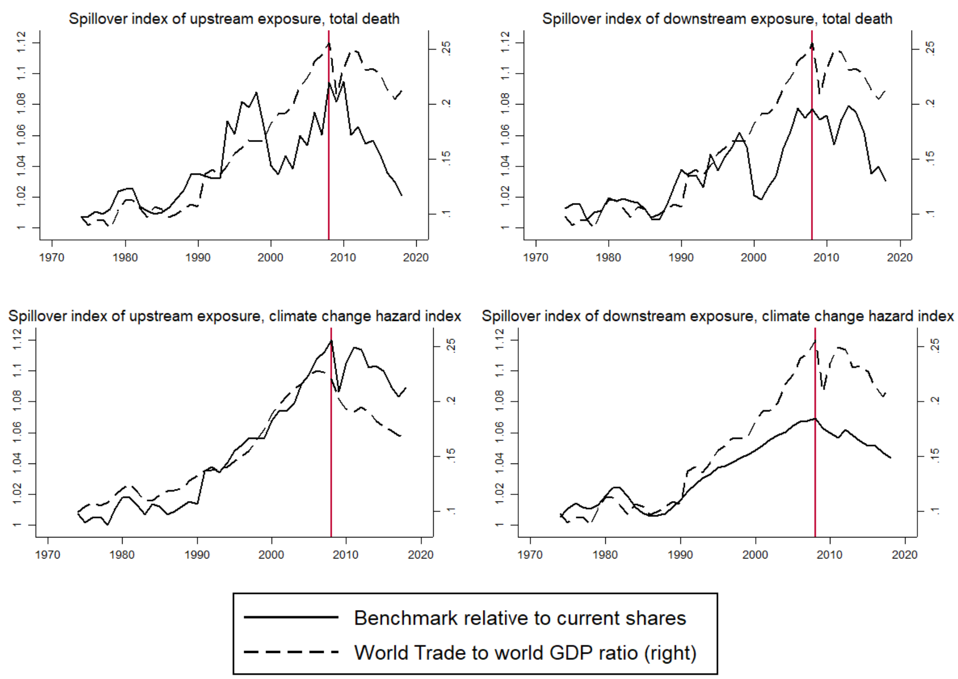
Figure 2 plots the time series of the spillover indexes for both upstream and downstream exposures to global climate disaster damages and climate risks. Climate disaster damages are measured in terms of number of deaths, while climate risks are measured with the climate change hazard index.[28] On the right axis, the figure plots the world trade-to-world GDP ratio. The trends of the two plots closely follow one another. This indicates that deepening globalization increases the spillovers of climate disasters and climate risks

[27] For example, from 1971 to 2008, cross-country dispersion (standard deviation) of global climate disaster damage exposures declined by 6.3% for upstream shocks and 10.7% for downstream shocks, relative to their respective levels in 1971. Disaster damages are measured in terms of number of deaths.

[28] Other measures of climate disaster damages and climate risks yield similar results.

across borders, and reduces the dispersion of climate shock exposures across countries.[29]

Figure 2: Global spillover indexes of exposures to climate disasters and climate risks




The figures plot the global spillover indexes of exposures to climate disasters and climate risks. Climate disasters are measured with total deaths. Climate risks are measured with the climate change hazard index. The global spillover indexes take a three-year moving average. The vertical line marks 2008–the financial crisis.

Before moving on to estimating the financial market implications of exposures to foreign climate disasters, we draw attention to the welfare consequences of the cross-border spillovers that occur with international trade. Our framework implies that globalization reduces the cross-country dispersion of the damage from climate disasters. This would potentially lead to positive-sum global welfare gains if the utility function of each country's representative consumer is concave. In this case, it would be beneficial from a global perspective if exposures to climate disasters are smoothed out between countries, and extreme losses from climate disasters are avoided. We leave the modeling of welfare implications of the cross-border spillovers to future research.[30]

[29] Appendix Section A.2 presents another way to understand globalization's contribution, where we investigate the fraction of the reduction in cross-country dispersion in climate shock exposures that could be explained by variations in trade shares and variations in climate shocks.

[30] We also note that global trade can bring about economic benefits to all countries and lead to spatial reallocation of workers and industries that adapt to climate change (for example, Cruz et al. 2020). Both channels enhance the level of climate resilience of all countries and should be taken into consideration when a general equilibrium model for global trade and climate change is constructed.

# 4 Equity returns and foreign climate disasters: event study

We now investigate the impact of exposures to foreign climate disasters on the stock market returns of the home country. We use an event study approach designed as follows. Consider the downward spillover of an upstream disaster. In the first step, for each disaster $d$ in the ED-MAT database, we link the country hit by the disaster, $i(d)$, with the country to which $i(d)$ exports the largest value of output. We label this county $n_D\left(i\left(d\right)\right)$. Using math,

$$n_D\left(i\left(d\right)\right) = argmax_{n_D \neq i} S_{n_D i(d),y(d)}$$

We then study the impact of the disaster $d$ on the stock market valuation responses in country $n_D\left(i\left(d\right)\right)$ around the date that disaster $d$ hit $i\left(d\right)$. We use this as a quantification of the impact of upstream climate disasters on the downstream stock market. Based on Section 3.1, if the output share of country $i$ to $n_D$ is denoted $S_{n_D i(d),y(d)}$ and the disaster damage is denoted $Damage_{i(d)}$, the loss in sales from $i$ to $n_D$ is measured with $S_{n_D i(d),y(d)}\ Damage_{i(d)}$. Therefore, $n_D\left(i\left(d\right)\right)$ should be the downstream foreign country that bears the largest value of damage from disaster $d$.[31] If we do not observe a significant response to the disaster in $n_D$'s stock market, we probably will not see a significant response in $i$'s smaller exporting destinations, either.[32] In fact, as a placebo test, we find that, on average, an upstream climate disaster does not lead to a significant stock market response in the disaster-hit country's 35th largest (median) exporting destination (Appendix Figure B.2b).

We use a similar approach to study the upward spillover of a climate disaster $d$ that hits downstream country $n$. We investigate the stock market response in the upstream country $i_U$, from which country $n$ imports the largest value:

$$i_U\left(n\left(d\right)\right) = argmax_{i_U \neq n} \pi_{n(d) i_U,y(d)}$$

Remember, if the expenditure share of country $n$ on $i_U$ is $\pi_{n(d)i_U,y(d)}$ and if the disaster damage is $Damage_{n(d)}$, the reduction in imports from $i_U$ by $n$ caused by disaster $d$ equals $\pi_{n(d)i_U,y(d)} Damage_{n(d)}$. Then $i_U\left(n\left(d\right)\right)$ should be the upstream foreign country that bears

[31] On average, a country sells about 3.1% of its gross output to its largest exporting destination. See Table A.4.

[32] De Souza and Li (2020) employs a similar approach to study the labor market implications of upstream and downstream tariffs through input-output linkages. They link the upstream tariffs to the downstream sector to which the tariffed sector sells the largest fraction of output, and they link the downstream tariffs to the upstream sector from which the tariffed sector buys the largest share from.

the largest value of damage from the disaster.[33] Therefore, compared to other importing origins, $i_U$ country should respond more significantly to the disaster. We also conduct a placebo test that shows that on average a downstream climate disaster does not lead to a significant stock market response in the disaster-hit country's 35th largest (median) importing origin (Appendix Figure B.2a).

After we link each disaster $d$ with the largest exporting destination $n_D$ and the largest importing origin $i_U$ of the country that is hit by the disaster,[34] we conduct event studies of the disasters on the upstream and downstream countries' stock markets. Here we illustrate the specification with $n_D$. We acquire the specification for $i_U$ if we replace every $n_D$ with $i_U$.

We focus on the response of the aggregate market and sector-level stock indexes. Use $RE^s_{n_D,t}$ to denote the stock index return of sector $s$[35] in country $n_D$ on day $t$. The excess return is defined as: $re^s_{n_D,t} = RE^s_{n_D,t} - r^f_{n_D,t}$, where $r^f_{n_D,t}$ is the three-month government bond yield in country $n_D$. We estimate the expected return for individual sectors as follows:

$$re^s_{n_D,t} = \beta^s_{0,n_D} + \beta^s_{1,n_D} re^s_{global,t} + \beta^s_{2,n_D} re^{mkt}_{n_D,t} + \epsilon^s_{n_D,t}$$

, where $re^s_{global,t}$ is the excess return in the global stock index of sector $s$ (in excess of the three-month Treasury bill yield by the US). $re_{n_D,t}$ is the country-level aggregate market excess return in country $n_D$ (in excess of the three-month government bond yield in country $n_D$). To estimate the expected return for the aggregate market, we use the following specification:

$$re^{mkt}_{n_D,t} = \beta^{mkt}_{0,n_D} + \beta^{mkt}_{1,n_D} re^{mkt}_{global,t} + \epsilon^{mkt}_{n_D,t}$$

We estimate the model on a window that starts 12 months before the date of each disaster $t(d)$ and ends one month before the disaster. We estimate the model for each disaster and acquire the disaster-specific coefficients. The estimated coefficients $\widehat{\beta^s_{0,n_D}}$, $\widehat{\beta^s_{1,n_D}}$, $\widehat{\beta^s_{2,n_D}}$[36] relate the expected return in an individual country-sector pair to the sector's return on the world level and the country-level aggregate market return. Using the estimated coefficients, we compute the daily abnormal return in the event window. The event window is defined to start 21 trading days before the disaster occurs and to end 60 trading days

[33] On average, a country spends about 2.7 percent of its total expenditure on its largest importing source. See Table A.4.

[34] From now on, we use $n_D$ as the shorthand for $n_D(i(d))$ and $i_U$ as the shorthand for $i_U(n(d))$.

[35] The aggregate market is denoted with $s = mkt$.

[36] $\widehat{\beta^{mkt}_{0,n_D}}$, $\widehat{\beta^{mkt}_{1,n_D}}$ for the aggregate market.

after the disaster occurs; thus, we capture any anticipation effect that occurs prior to the disaster.

$$AR^{s}_{n_D,t} = re^{s}_{n_D,t} - \widehat{\beta^{s}_{0,n_D}} - \widehat{\beta^{s}_{1,n_D}} re^{s}_{global,t} - \widehat{\beta^{s}_{2,n_D}} \, re^{mkt}_{n_D,t}$$

$$AR^{mkt}_{n_D,t} = re^{mkt}_{n_D,t} - \widehat{\beta^{mkt}_{0,n_D}} - \widehat{\beta^{mkt}_{1,n_D}} re^{mkt}_{global,t}$$

The $x$-day cumulative abnormal return in country $n_D$ due to disaster $d$ is defined as: $CAR^{s}_{n_D,x} = \sum_{\tau=t(d)-21}^{t(d)\,+\,x} AR^{s}_{n_D,\tau}$ (with normalization $CAR^{s}_{n_D,-21} = 0$). We compute these for each disaster. Then we compute the mean of all disasters: $\overline{CAR}^{s}_{x}$ and their 95 percent confidence intervals.

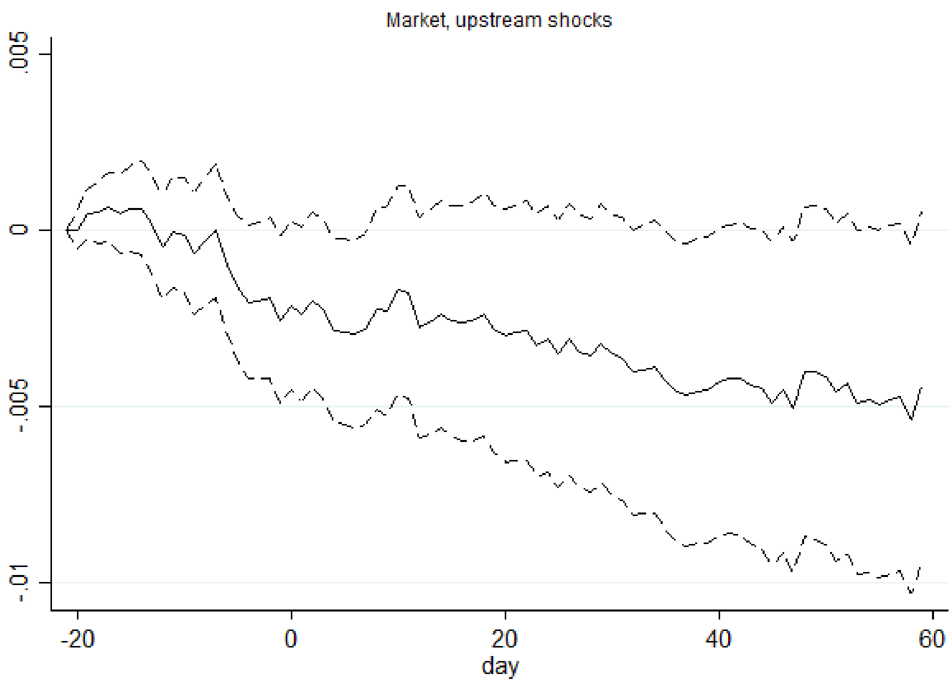
Figures 3 shows that the 40-day (from 21 trading days before the disaster to 40 trading days after the disaster) aggregate market-level cumulative abnormal returns to upstream and downstream climate disasters are both about -0.5% and are significant at 95 percent confidence interval around 35 trading days after the disaster starts. The magnitude is comparable to the impact of a climate disaster on the home country's stock market (about -1 percent) in the GFSR.[37]

Figure B.3 plots the cumulative abnormal returns for the spillovers of upstream climate disasters on downstream sectoral stock market indexes. Figure B.4 plots the cumulative abnormal returns for the spillovers of downstream climate disasters on the upstream sectoral stock market indexes. These figures show that the sectoral stock market responses to foreign disasters differ substantially with respect to sectors. For example, the 40-day cumulative abnormal returns in the chemicals sector are -0.8 percent for upstream disasters and -1 percent for downstream disasters. The 40-day cumulative abnormal returns in the automobiles sector are as substantial as -1.8 percent for upstream disasters and -1.5 percent for downstream disasters. Conversely, the media sector, the telecommunication sector, and others do not respond significantly to foreign disasters. We observe that most sectors traditionally considered tradable have significantly negative cumulative abnormal returns from foreign disasters, while most sectors traditionally considered non-

[37]The estimated stock market impact of the average foreign disaster refers to the response in the disaster-hit country's largest exporting and importing partners. If we want to get the total foreign spillover of a disaster, we need to aggregate up the ripple effects in all foreign countries that trade with the disaster-hit country. If we want to get the aggregate effect of all foreign disasters to a country, we need to aggregate up all disasters that affect the country's trading partners. Constrained by computing power and given that we are undertaking a partial equilibrium analysis, we leave the add-up to future works. The total effect of a disaster on all foreign economies and the total loss of a country from all foreign disasters should be even more negative.

Figure 3: Climate disasters significantly undermine the stock market returns in main importing and exporting partners of the countries hit by climate disasters

(a) Market, upstream disaster




(b) Market, downstream disaster


The figures plot cumulative abnormal returns in the stock market indexes in the main exporting destination of the upstream disaster-hit country and the main importing origin of the downstream disaster-hit country from 20 days before the disaster to 60 days after the disaster.

tradable do not. These first results raise the possibility that tradable sectors are affected more negatively than non-tradable sectors. We discuss the relationship between sector tradability and the stock market valuation response to foreign disasters in Section 5.1.

We have interpreted the impact of upstream climate disasters on the downstream stock market as a negative foreign supply shock and the impact of downstream climate disasters on the upstream stock market as a negative foreign demand shock. However, because global supply chains are complicated, other channels through which upstream and downstream shocks affect the domestic market may exist. For example, upstream suppliers might compete with domestic suppliers. If the upstream competitors are impacted by their disasters, domestic suppliers might expand, leading to a gain in stock prices. Downstream consumers, if impacted by a climate disaster, may spend less due to an income loss; yet they may also need to rebuild, and such expenditure might have an expansionary effect on the upstream foreign country. The latter can increase the upstream stock price. Therefore, where there is this bias, our estimates should be biased upward because they include the positive contributions by the two alternative channels. Given that we find negative total effects from foreign disasters for the market and the tradable sectors, the two confounding stories strengthen the main channels that we propose.

To emphasize international trade's key role in propagating climate disaster damages across borders we perform a placebo test. We plot out the cumulative abnormal return in the event windows for the 35th largest (median) importing-exporting partner of the country hit by the disaster. The results are shown in Figure B.2. The 35th largest importer and exporter's stock market, both at the market aggregate and the sector level, does not respond significantly to the disaster.

# 5 Equity returns and foreign climate disasters: cross-sectional analysis

Section 4 shows that the cross-border spillovers of climate disasters reduce country-level aggregate market returns and can significantly reduce the returns of many tradable sectors. In this section, using a cross-sectional analysis at the disaster level, we associate the magnitude of these cumulative abnormal returns with the foreign disaster damage, the trade shares, and size of the domestic economy. We further show that sectoral cumulative abnormal returns due to the same foreign disaster are negatively associated with sector tradability. This section also explores the extent to which spillovers of foreign climate disasters affect the stability of financial sectors.

Remember the measure of exposures to foreign climate disasters that we present in Section 3.1. The EM-DAT data contains information about the direct monetary loss from a climate disaster $d$ in upstream country $i$. Denote this variable with $Damage_{i(d)}$. The loss in sales from $i$ to $n_D$ from this disaster is then measured with $S_{n_D i(d),y(d)}\ Damage_{i(d)}$, where $S_{n_D i(d),y(d)}$ refers to the output share of country $i$ to country $n_D$ in year $y\left(d\right)$. The stock market return is a relative measure of the total valuation of the economy of interest. To determine the monetary damage relative to the size of the economy, we normalize the loss in sales with the GDP of country $n_D$ to obtain the normalized damage of the upstream disaster:

$$nor\_up\_damage_{n_D(d),y(d)} = \frac{S_{n_D i(d),y(d)}\ Damage_{i(d)},}{GDP_{n_D,y(d)}} \tag{1}$$

Given the monetary loss in sales that spills across borders, the larger is the size of home economy, the smaller is the ripple of the upstream shock in home country's stock market. Similarly, we construct the measure for normalized damage of a downstream disaster. Having measured the direct disaster loss for the downstream country in monetary values, $Damage_{n(d)}$ and the expenditure share $\pi_{n(d),i_U y(d)}$, which is the loss in purchase by $n$ from $i_U$, equals $\pi_{n(d),i_U y(d)}\ Damage_{n(d)}$. Then we normalize the loss with $i_U$'s GDP:

$$nor\_down\_damage_{i_U(d),y(d)} = \frac{\pi_{n(d),i_U y(d)}\ Damage_{n(d)}}{GDP_{i_U,y(d)}}$$

To study the association between the magnitude of an upstream foreign disaster and the cumulative abnormal return in the home country's stock market, we first consider the following specification (the specification of downstream disasters replaces $n_D$ with $i_U$ and the normalized upstream damage with the normalized downstream damage):

$$CAR^s_{n_D(d),40} = \alpha^s_1\ nor\_upstr\_damage_{n_D(d),y(d)} + \delta^s_{n_D} + \gamma^s_y + \epsilon^s_d$$

We regress the cumulative abnormal return of trading day 40 (from 21 trading days before the disaster to 40 trading days after the disaster) in the home country sector $s$ ($s$ refers to individual sectors or the country-level aggregate market) stock index, on the normalized upstream damage. $CAR^s_{n_D(d),40}$ denotes the cumulative abnormal return of each climate disaster that we compute in Section 4. $\alpha^s_1$ captures changes in sectoral cumulative abnormal returns associated with changes in exposures to foreign disaster damages relative to domestic GDP. We control for the home-country fixed effect to reflect the possibility that countries might differ in their abilities to hedge the spillovers of foreign climate shocks. We also control for the year fixed effect. To account for potential correlation within the same stock market and within the same year, we cluster standard errors with two-way clustering on the stock market and year level. We run this regression sector by sector, allowing for the coefficients, especially $\alpha_1^s$, to be different across sectors.

Table 1 shows the results for upstream climate disasters. The home-country stock market index return is negatively associated with the size of the upstream disaster. A 0.1 percent increase in the exposure of the home country's GDP to foreign upstream climate disaster damage is associated with a 5.9 percent decline in the cumulative abnormal return in market-wide trading on day 40.[38] Table 1 also illustrates sector heterogeneity in the response to the size of upstream shocks. The impact on most tradable sectors–for example, automobile, basic materials, chemicals, food and beverages, food producers, industrial goods, and industrial producers–is negative and significant. An increase in foreign upstream damage of 0.1 percent of home-country GDP is associated with a more than 10 percent decline in the stock market valuations in the automobile and chemical sectors. Conversely, the cumulative abnormal returns in most non-tradable sectors are not significantly affected by upstream damages. In Section 5.1 we further investigate the relationship between sector tradability and the response to foreign climate shocks.

The results for downstream climate disasters are reported in Table 2. The correlation between cumulative abnormal return in the home-country market and the size of downstream disasters is also negative and significant. A 0.1 percent increase in the exposure of the home country's GDP to downstream foreign climate disaster damage is associated with a 3.7 percent decline in the market-level cumulative abnormal return on trading day 40.[39] Like the upstream results, the typical tradable sectors respond more negatively and more significantly to the magnitude of the downstream disasters than most non-tradable sectors.

## 5.1 Tradability and the cross-border spillover of climate disasters

Next, we formally investigate the relationship between sector tradability and sectoral cumulative abnormal returns from foreign disasters. If climate disasters propagate across

[38]One standard deviation increase in the normalized upstream damage is associated with 0.0125 standard deviation decrease in the market-wide, 40-day cumulative abnormal return. The inter-quartile increase in the normalized upstream damage is associated with 0.01% decrease in the cumulative abnormal return of the downstream market. See Table 1.

[39]One standard deviation increase in the normalized downstream damage is associated with 0.0049 standard deviation decline in the market-level cumulative abnormal return. The inter-quartile increase in the normalized downstream damage corresponds to 0.01% decrease in the cumulative abnormal return of the upstream market. See Table 2.

Table 1: Cross-sectional analysis: association between magnitude of upstream climate disaster and sectoral cumulative abnormal return

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| VARIABLES | MRKTS | AUTMB | BANKS | BMATR | BRESR | CHMCL | CNSTM |
| nor_up_damage | -58.81** | -195.9*** | 31.38 | -79.00*** | 4.902 | -132.0*** | -51.23 |
| | (21.61) | (60.71) | (28.03) | (9.482) | (27.33) | (24.42) | (49.71) |
| Observations | 4,959 | 4,932 | 4,937 | 4,959 | 4,950 | 4,957 | 4,938 |
| FE | n; y | n; y | n; y | n; y | n; y | n; y | n; y |
| Cluster | n; y | n; y | n; y | n; y | n; y | n; y | n; y |
| $\Delta sd$ | -0.0125 | -0.0273 | 0.00699 | -0.0171 | 0.000756 | -0.0237 | -0.00927 |
| $\Delta interq$ | -0.000156 | -0.000520 | 8.33e-05 | -0.000210 | 1.30e-05 | -0.000350 | -0.000136 |
| | (8) | (9) | (10) | (11) | (12) | (13) | (14) |
| VARIABLES | FDBEV | FINSV | FOODS | HHOLD | HLTHC | INDGS | INDUS |
| nor_up_damage | -98.41** | -32.35 | -96.22* | -34.81 | -68.01 | -42.11*** | -69.95*** |
| | (43.88) | (33.10) | (52.50) | (210.2) | (41.90) | (13.55) | (13.77) |
| Observations | 4,874 | 4,706 | 4,382 | 3,806 | 4,898 | 4,959 | 4,959 |
| FE | n; y | n; y | n; y | n; y | n; y | n; y | n; y |
| Cluster | n; y | n; y | n; y | n; y | n; y | n; y | n; y |
| $\Delta sd$ | -0.0198 | -0.00754 | -0.0210 | -0.00700 | -0.0133 | -0.0122 | -0.0199 |
| $\Delta interq$ | -0.000261 | -8.58e-05 | -0.000255 | -9.24e-05 | -0.000181 | -0.000112 | -0.000186 |
| | (15) | (16) | (17) | (18) | (19) | (20) | (21) |
| VARIABLES | INSUR | LFINS | MEDIA | NLINS | PCINS | REINS | RLEST |
| nor_up_damage | -75.22 | -70.93 | 33.58 | -22.93 | -58.24 | -325.2 | -54.24 |
| | (46.12) | (56.77) | (77.50) | (58.01) | (61.63) | (299.6) | (57.20) |
| Observations | 4,937 | 4,517 | 4,753 | 4,887 | 4,766 | 2,719 | 4,859 |
| FE | n; y | n; y | n; y | n; y | n; y | n; y | n; y |
| Cluster | n; y | n; y | n; y | n; y | n; y | n; y | n; y |
| $\Delta sd$ | -0.0162 | -0.0120 | 0.00482 | -0.00431 | -0.00879 | -0.0568 | -0.00860 |
| $\Delta interq$ | -0.000200 | -0.000188 | 8.91e-05 | -6.08e-05 | -0.000155 | -0.000863 | -0.000144 |
| | (22) | (23) | (24) | (25) | (26) | | |
| VARIABLES | RTAIL | TECNO | TELCM | TRLES | UTILS | | |
| nor_up_damage | -42.62 | 42.05 | 91.11 | -46.15 | 1.003 | | |
| | (69.39) | (46.22) | (57.21) | (37.86) | (29.42) | | |
| Observations | 4,937 | 4,503 | 4,860 | 4,755 | 4,858 | | |
| FE | n; y | n; y | n; y | n; y | n; y | | |
| Cluster | n; y | n; y | n; y | n; y | n; y | | |
| $\Delta sd$ | -0.00737 | 0.00659 | 0.0157 | -0.00630 | 0.000197 | | |
| $\Delta interq$ | -0.000113 | 0.000112 | 0.000242 | -0.000123 | 2.66e-06 | | |

Robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

This table shows the association between normalized upstream disaster damage and trading day 40's (from 21 trading days before the disaster to 40 trading days after the disaster) cumulative abnormal return in the downstream stock market for individual sectors. The regressions control for the the downstream country (of which we study the stock market response) and year fixed effects. Standard errors are two-way clustered on the stock market and year level. Row $\Delta sd$ refers to the change in standard error of the dependent variable associated with one standard deviation increase in the independent variable. Row $\Delta interq$ refers to the changes in the magnitude of the dependent variable associated with raising the independent variable from its 25th percentile to 75th percentile.

Table 2: Cross-sectional analysis: association between magnitude of the downstream climate disaster and sectoral cumulative abnormal return

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| VARIABLES | MRKTS | AUTMB | BANKS | BMATR | BRESR | CHMCL | CNSTM |
| nor_down_damage | -37.25* | -133.4*** | -0.854 | -46.73** | 8.032 | -115.9*** | -24.88 |
| | (20.57) | (26.29) | (23.67) | (20.77) | (46.50) | (12.17) | (31.56) |
| Observations | 4,414 | 4,364 | 4,404 | 4,414 | 4,401 | 4,391 | 4,385 |
| FE | n; y | n; y | n; y | n; y | n; y | n; y | n; y |
| Cluster | n; y | n; y | n; y | n; y | n; y | n; y | n; y |
| $\Delta sd$ | -0.00491 | -0.0124 | -0.000143 | -0.00731 | 0.000951 | -0.0132 | -0.00317 |
| $\Delta interq$ | -0.000145 | -0.000519 | -3.32e-06 | -0.000182 | 3.12e-05 | -0.000451 | -9.68e-05 |
| | (8) | (9) | (10) | (11) | (12) | (13) | (14) |
| VARIABLES | FDBEV | FINSV | FOODS | HHOLD | HLTHC | INDGS | INDUS |
| nor_down_damage | -76.52** | -48.79 | -75.55* | -179.8 | 20.34 | -47.72* | -73.54** |
| | (34.06) | (32.51) | (38.41) | (214.6) | (55.81) | (23.75) | (25.58) |
| Observations | 4,330 | 3,976 | 3,398 | 3,000 | 4,354 | 4,414 | 4,407 |
| FE | n; y | n; y | n; y | n; y | n; y | n; y | n; y |
| Cluster | n; y | n; y | n; y | n; y | n; y | n; y | n; y |
| $\Delta sd$ | -0.0100 | -0.00750 | -0.0117 | -0.0266 | 0.00249 | -0.00859 | -0.0131 |
| $\Delta interq$ | -0.000298 | -0.000190 | -0.000294 | -0.000700 | 7.91e-05 | -0.000186 | -0.000286 |
| | (15) | (16) | (17) | (18) | (19) | (20) | (21) |
| VARIABLES | INSUR | LFINS | MEDIA | NLINS | PCINS | REINS | RLEST |
| nor_down_damage | -56.41** | -61.97* | 45.20 | -40.17 | -106.3* | -715.3* | -18.94 |
| | (25.52) | (31.33) | (70.58) | (33.20) | (51.90) | (315.2) | (43.18) |
| Observations | 4,374 | 3,605 | 4,027 | 4,286 | 4,148 | 1,896 | 4,309 |
| FE | n; y | n; y | n; y | n; y | n; y | n; y | n; y |
| Cluster | n; y | n; y | n; y | n; y | n; y | n; y | n; y |
| $\Delta sd$ | -0.00856 | -0.00770 | 0.00349 | -0.00464 | -0.0101 | -0.0932 | -0.00196 |
| $\Delta interq$ | -0.000219 | -0.000241 | 0.000176 | -0.000156 | -0.000414 | -0.00278 | -7.37e-05 |
| | (22) | (23) | (24) | (25) | (26) | | |
| VARIABLES | RTAIL | TECNO | TELCM | TRLES | UTILS | | |
| nor_down_damage | -18.27 | 76.44* | 61.64 | -30.94 | 59.70 | | |
| | (31.70) | (41.00) | (57.93) | (46.45) | (55.24) | | |
| Observations | 4,339 | 3,634 | 4,301 | 4,194 | 4,332 | | |
| FE | n; y | n; y | n; y | n; y | n; y | | |
| Cluster | n; y | n; y | n; y | n; y | n; y | | |
| $\Delta sd$ | -0.00196 | 0.00744 | 0.00683 | -0.00267 | 0.00766 | | |
| $\Delta interq$ | -7.11e-05 | 0.000297 | 0.000240 | -0.000120 | 0.000232 | | |

Robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

This table shows the association between normalized downstream disaster damage and trading day 40′s (from 21 trading days before the disaster to 40 trading days after the disaster) cumulative abnormal return in the upstream stock market for individual sectors. The regressions control for the the upstream country (of which we study the stock market response) and year fixed effects. Standard errors are two-way clustered on the stock market and year level. Row $\Delta sd$ refers to the change in standard error of the dependent variable associated with one standard deviation increase in the independent variable. Row $\Delta interq$ refers to the changes in the magnitude of the dependent variable associated with raising the independent variable from its 25th percentile to 75th percentile.

country borders where international trade occurs, we expect that the sectors that are more tradable in terms of importing will respond more negatively to upstream climate disasters. The reason is that these sectors import a relatively larger share of input from abroad than the non-tradable sectors do. Given the magnitude of a particular disaster, the input to these sectors should face larger damage than the sectors that import little input from abroad. Conversely, the sectors that are more tradable in terms of exporting will respond more negatively to downstream climate disasters. Before proceeding to the main specification, we first consider a pooled regression of the previous sector-level regression that collects all sectors. We control the home country, year, and sector fixed effects. In doing so, we recover the average association between the cumulative abnormal return and the normalized upstream and downstream damage (here we use upstream disasters as an example):

$$CAR^s_{n_D(d),40} = \alpha\, nor\_upstr\_damage_{n_D(d),y(d)} + \delta_{n_D} + \gamma_y + \zeta^s + \epsilon^s_d$$

Table 3, Columns 1–2 show that for the average sector, the cumulative abnormal return is negatively correlated with the size of the upstream and downstream disasters. A 0.1 percent increase in the upstream and in the downstream exposure of the home-country GDP is associated with a 4.7 percent decline and a 3.3 percent decline, respectively, in sectoral cumulative abnormal return on trading day 40.[40]

In the next step, we investigate sectoral heterogeneity in their response to exposures to foreign disasters. We run a panel regression of the cumulative abnormal return, on the level of the normalized upstream damage, and the interaction between the normalized upstream damage and the importing tradability. Remember, we use $TDIM^s$ to denote the sectoral importing tradability:

$$\begin{aligned} CAR^s_{n_D(d),40} = {} & \mu\, nor\_upstr\_damage_{n_D(d),y(d)} + \lambda\, nor\_upstr\_damage_{n_D(d),y(d)} * TDIM^s \\ & + \delta_{n_D} + \gamma_y + \zeta^s + \epsilon^s_d \end{aligned}$$

We control for the country fixed effect for the country that is hit by the disaster and the year fixed effect. To take out the level effect of importing tradability on the cumulative abnormal returns we also control the sector fixed effect. To study the impact of exporting tradability on the cumulative abnormal returns from downstream disasters, we consider the corresponding regression equation. Remember, we use $TDEX^s$ to denote the sectoral

[40] One standard deviation increase in the size of the upstream disaster and the downstream disaster corresponds to 0.0653 and 0.0251 standard deviation decline in sectoral cumulative abnormal return of an average sector. See Table 3.

exporting tradability:

$$CAR^s_{i_U(d),40} = \mu \, nor\_upstr\_damage_{i_U(d),y(d)} + \lambda \, nor\_upstr\_damage_{i_U(d),y(d)} * TDEX^s + \delta_{i_U} + \gamma_y + \zeta^s + \epsilon^s_d$$

Column 3 of Table 3 shows that as soon as we control for the interaction between the upstream damage and the importing tradability, the level effect of the upstream damage becomes insignificant. Meanwhile, the interaction between the upstream damage and the importing tradability is strongly significantly correlated with the cumulative downstream damage. Column 4 of Table 3 shows that when we control for the interaction between the downstream damage and the exporting tradability, the level effect of the downstream damage also becomes insignificant, and the interaction term is significantly negative. These findings indicate that the negative impact of the upstream and downstream disaster damage for the average sector is entirely driven by the tradable sectors.

The estimated coefficients imply, for example, that a 0.1 percent increase in the exposure of upstream foreign climate disaster relative to home-country GDP is predicted to reduce the cumulative abnormal returns by 15.4 percent in the sector that has the highest importing tradability (chemicals), 4.1 percent in the sector that has the median importing tradability (food and beverages), and 0.98 percent in the sector that has the lowest importing tradability (real estate).[41] A 0.1 percent increase in the exposure of downstream foreign climate disaster relative to home-country GDP is predicted to reduce the cumulative abnormal returns by 9.5 percent in the sector that has the highest exporting tradability (automobile), 2.2 percent in the sector that has the median exporting tradability (media), and 0.92 percent in the sector that has the lowest exporting tradability (real estate).[42]

Other international linkages, for example, financial spillover through global capital flows, geographical spread of natural disasters to nearby countries, dual listings of stocks, etc., may allow a country's financial market to be affected by disasters that happen in other countries. The cross-border propagation of climate disasters through international trade and supply chain linkages that we identify is not likely driven by these confounding channels. The alternatives do not have asymmetric effects either between major trade partners and other countries (for example, global capital flows, dual stock listings) or

[41]One standard deviation increase in the normalized upstream damage for the sector with median importing tradability (food and beverages) is associated with 0.0473 standard deviation declines in the cumulative abnormal returns. See Table 3.

[42]One standard deviation increase in the normalized downstream damage for the sector with median exporting tradability (media) is associated with 0.0143 standard deviation declines in the cumulative abnormal returns. See Table 3.

Table 3: Cross-sectional analysis: association between sector tradability and sectoral cumulative abnormal return due to a foreign climate disaster

| VARIABLES | (1)<br>CAR40 | (2)<br>CAR40 | (3)<br>CAR40 | (4)<br>CAR40 |
|---|---|---|---|---|
| nor_up_damage | -47.20** | | -6.775 | |
| | (22.43) | | (30.80) | |
| nor_down_damage | | -32.67* | | -8.964 |
| | | (16.37) | | (16.07) |
| nor_up_d * TDIM | | | -246.5*** | |
| | | | (56.28) | |
| nor_down_d * TDEX | | | | -83.74*** |
| | | | | (18.96) |
| Observations | 122,576 | 106,127 | 122,576 | 106,127 |
| FE | n; y; s | n; y; s | n; y; s | n; y; s |
| Cluster | n; y | n; y | n; y | n; y |
| $\Delta sd$ | -0.0653 | -0.0251 | -0.0473 | -0.0143 |
| $\Delta interq$ | -0.000125 | -0.000127 | -9.07e-05 | -7.21e-05 |

Robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

This table shows the association between sector tradability and trading day 40's (from 21 trading days before the disaster to 40 trading days after the disaster) cumulative abnormal return due to a foreign climate disaster. Column 1 considers a pooled regression of all sectors on normalized upstream disaster damage. Column 2 considers a pooled regression of all sectors on normalized downstream disaster damage. Column 3 adds to column 1 an interaction term between normalized upstream damage and sector importing tradability. Column 4 adds to column 2 an interaction term between normalized downstream damage and sector exporting tradability. The regressions control for stock market, year, and sector fixed effects. Standard errors are two-way clustered on the stock market and year level. In columns 1–2, row $\Delta sd$ refers to the change in standard error of the dependent variable associated with one standard deviation increase in the independent variable. In columns 3–4, row $\Delta sd$ refers to the change in standard error of the dependent variable associated with one standard deviation increase in the normalized damage, for sectors with median tradability. In columns 1–2, row $\Delta interq$ refers to the change in the magnitude of the dependent variable associated with raising the independent variable from its 25th percentile to 75th percentile. In columns 3–4, row $\Delta interq$ refers to the change in the magnitude of the dependent variable associated with raising the independent variable from its 25th percentile to 75th percentile, for sectors with median tradability.

between tradable sectors and other sectors (for example, geographical spillovers). Yet in robustness tests that we discuss above, we find that foreign climate disasters do not significantly affect non-major trade partners or non-tradable sectors. We recognize that these other possible channels may help propagate climate risks as well—we leave them for future research.

### 5.2 Climate disaster spillovers and the financial sector

The GFSR finds that home-country climate disasters reduce the valuation of financial sector stocks. This indicates either that the revenue of the financial sector declines or that the risk associated with the financial sector rises. In either case, the financial stability of the home country is undermined. The GFSR also finds that insurance penetration and sovereign rating upgrade improve the financial sector valuations, holding fixed the magnitude of the disasters. The channels through which foreign climate disasters affect a country's financial stability are different from home-country disasters. The home-country disasters damage the infrastructure, properties, and personnel, thus directly affecting the financial sector's operations, and they affect almost all clients of the financial sector. Foreign climate disasters affect financial stability indirectly because most of the ramifications of foreign climate disasters are loaded on the tradable sectors.

In this section, we explore whether the impact of foreign disasters on the financial sector valuation at home depends on country institutional factors. We examine two factors: the degree of international factoring–a form of protection for domestic traders[43]–and banking sector capitalization. We predict that an increase in domestic trader protection leads to smaller losses in domestic financial sectors from foreign disasters because it reduces the loss of domestic exporters and importers from foreign disasters and their probability to default on financial sector loans. An increase in domestic banking sector strength allows the financial sector to contain the defaults in its clients–the tradable sectors–and may too lead to smaller losses in domestic financial sectors from foreign disasters.

To measure the degree of trade protection, we use the variable: the ratio of factoring volume to GDP. To measure banking capitalization, we use the standard variable: the ra-

[43]Factoring refers to selling a business' outstanding receivables (commonly due within 90 days) to the factor (generally a financial institution, like a bank) at a discount. The business then receives advance payment from the factor. The buyer's factor then handles the collection and payment of the account receivable with the buyer. Factoring is extensively used in international transactions. Factoring protects upstream exporters. Consider a disaster that hits the downstream country. Without access to factoring, the exporter bears all the risk if the importer defaults. If the exporter fails to collect payment from the downstream and if the exporter is financially constrained, it may default on its banks. Factoring service, on the other hand, transfers the risk to the importer's factor. Therefore, it protects the exporting country from default risks related to the importer. Factoring defends downstream country against upstream climate disasters, too. The importer only needs to pay its factor after the upstream seller makes the shipment and transfers the account receivable. Therefore, the importer does not have to pay the exporter prior to the shipment, avoiding the default risks of the seller. See this link.

tio of the bank regulatory capital-to-risk-weighted assets.[44] Following the GFSR, we take a one-year lag of the institutional variables to alleviate potential endogeneity concerns. We consider the following specification for the downstream country (to study the financial sector cumulative abnormal return to downstream disasters, replace $CAR^{FIN}_{n_D(d),40}$ and $nor\_upstr\_damage_{n_D(d),y(d)}$ with their downstream counterparts):

$$CAR^{FIN}_{n_D(d),40} = \alpha\, nor\_upstr\_damage_{n_D(d),y(d)} + \beta\, factoring\_to\_GDP_{n_D,y(d)} + \epsilon^s_d$$

$$CAR^{FIN}_{n_D(d),40} = \alpha\, nor\_upstr\_damage_{n_D(d),y(d)} + \beta\, regulatory\_to\_assets_{n_D,y(d)} + \epsilon^s_d$$

Columns 1 and 3 of Table A.5 show that one percentage point increase in total factoring volume to GDP ratio is on average associated with about 0.1% increase in the cumulative abnormal returns from upstream and downstream climate disasters. According to Columns 2 and 4 of Table A.5, a 1 percentage point increase in the bank regulatory capital-to-risk-weighted assets ratio is associated with about a 0.2 percent increase in the cumulative abnormal return from upstream and downstream disasters.

# 6 Equity pricing of foreign climate change physical risk

Climate change leads to greater long-term risks of larger and more frequent climate disasters (the GFSR, BlackRock 2019, Woetzel et al. 2020). The risks differ across countries. For example, tropical countries may face a higher likelihood of heatwaves than countries in middle or high latitudes. Coastline countries may encounter larger sea-level rise and flood risks than inland countries. The major trading partners of high climate risk countries are exposed to these foreign climate risks through importing and exporting relationships. When these risks realize, according to the findings in Section 4 and 5, the stock returns in the home country will be negatively impacted. Forward-looking, rational investors should price these risks into the valuation of their portfolios.[45] They may thus observe a decline in stock market valuations at home when the home country is exposed to foreign climate risks. The GFSR studied the impact of home-country climate risks on stock valuations. Here we investigate whether exposure to foreign climate risks is associated with lower stock market valuations at home.

To measure foreign climate risk exposures, we slightly adapt the measures for expo-

[44] Find the definition through this link.

[45] If they have not priced in these risks (that is, if they have mispriced climate risks), a correction of mispricing will happen in the future and could be associated with financial stability risks.

sures to global climate risks that were introduced in Section 3.1. We identify a country's upstream foreign climate risk exposures by dropping the home-country trade shares from the measures:

$$U_{n,y} = \sum_{i \neq n} S_{ni,y} R_i \tag{2}$$

$R_i$ denotes the climate risks associated with country $i$. As in previous sections, $S_{ni,y}$ denotes the output shares by $i$ to $n$ in year $y$. If $S_{ni,y} = 0, \forall i \neq n$, then no foreign country will sell to country $n$. In this case, $U_{n,y} = 0$, which implies that country $n$ will not be exposed to upstream foreign climate risks at all. In our sample, all countries import from at least some foreign countries. Therefore, all countries are exposed to positive foreign upstream climate risks. Similarly, we obtain a country's downstream foreign climate risk exposures as follows:

$$D_{i,y} = \sum_{n \neq i} \pi_{ni,y} R_n \tag{3}$$

$\pi_{ni,y}$ denotes the expenditure shares by $n$ on $i$ in year $y$. If $\pi_{ni,y} = 0, \forall n \neq i$, no foreign country buys from country $i$. In this case, $D_{i,y} = 0$, which implies that country $i$ will not be exposed to upstream foreign climate risks. In our sample, all countries export to at least some foreign countries. Therefore, all countries are exposed to positive foreign downstream climate risks.

We consider the impact of exposures to foreign climate change risks on stock market P/E ratios in the home country on the sector level. These ratios are a forward-looking measure for long-term stock performance. To implement the empirical strategy, we first employ the same methodology as in the GFSR to take out the component in the P/E ratio that could be explained by the standard variables that may predict future stock price growth and volatility, including the interest rate ($r_{i,y}$, measured with the three-month government bond yield in the country of which the stock market we investigate), the expected future earnings ($EXPFE_{i,y}$, measured with the mean annual growth of earnings per share over the past five years), and the equity risk premium ($ERP_{i,y}$, measured with the standard deviation of annual growth of earnings per share over the past five years). To acquire the variables at the year level, we take the average of the monthly observations in the raw data. We run the following regressions sector by sector, for individual sectors and with $s = mkt$:

$$PE^s_{i,y} = a^s_0 + a^s_1 r_{i,y} + a^s_2 EXPFE_{i,y} + a^s_3 ERP_{i.y} + RPE^s_{i,y}$$

In the second step, we regress the residual P/E ratios predicted by the previous regression equation, $R\hat{P}E_i^s$, on the upstream and downstream exposures to foreign risks with a pooled regression of all sectors. To ensure comparability with the GFSR, we use a regression design with a cross section of countries, investigating whether the countries that are more exposed to foreign climate risks have lower price-to-earnings ratios. We fix the year $y = 2018$. We control for sector fixed effects (we only show the regression for upstream exposures; the regression for downstream exposures simply replaces $U_i$ with $D_i$):

$$RPE_i^s \ = \ b * U_i + \zeta^s + \epsilon_i^s \tag{4}$$

The results are presented in Columns 1–2 of Table 4. The home-country P/E ratio for the average sector is negatively associated with exposures to upstream and downstream foreign climate risks. A one standard deviation increase in the exposures to upstream and downstream foreign climate risks corresponds to about a 0.05 standard deviation decline in the P/E ratio. An inter-quartile increase in exposures to foreign risks is associated with a reduction in the P/E ratio of about 3.0 for upstream risks and about 3.7 for downstream risks.

We confirm that international trade is also the key spillover channel of foreign climate risks. We show that the tradable sectors are more negatively associated with the same foreign climate risks than the non-tradable sectors. As a set of examples, we first look at a typical tradable sector (the industrial producers sector) and a typical non-tradable sector (the real estate sector). We consider the following regressions:

$$RPE_i^{s=INDUS} = b_0^{s=INDUS} + b_1^{s=INDUS} * U_i + \epsilon_{i,t}^s$$

$$RPE_i^{s=RLEST} = b_0^{s=RLEST} + b_1^{s=RLEST} * U_i + \epsilon_{i,t}^s$$

Columns 3–6 of Table 4 show that the P/E ratios of the industrial producers sector are strongly negatively correlated with upstream and downstream foreign climate risks. There is no significant correlation between the real estate sector's P/E ratios and foreign climate risks.

Next, to study the role of sector tradability we include the interaction between the importing tradability and the upstream exposures to foreign climate risks as the regressor. We consider the following specification (we use the exporting tradability to interact with

Table 4: Association between exposure to foreign climate risks and home-country P/E ratio

| VARIABLES | (1)<br>Up<br>pooled | (2)<br>Down<br>pooled | (3)<br>Up<br>INDUS | (4)<br>Up<br>RLEST | (5)<br>Down<br>INDUS | (6)<br>Down<br>RLEST | (7)<br>Up<br>interaction |
|---|---|---|---|---|---|---|---|
| foreign_exp | -43.04*** | -43.94** | -16.63*** | -5.683 | -17.65*** | -4.623 | -9.687 |
| | (15.11) | (20.06) | (5.364) | (9.329) | (6.449) | (9.691) | (9.545) |
| foreign_exp * tradability | | | | | | | -200.3** |
| | | | | | | | (75.27) |
| Observations | 1,084 | 1,084 | 49 | 46 | 49 | 46 | 1,084 |
| FE | s | s | | | | | s |
| Cluster | n | n | | | | | n |
| | -0.0582 | -0.0541 | -0.176 | -0.0558 | -0.170 | -0.0413 | -0.0488 |
| | -3.024 | -3.731 | -1.168 | -0.399 | -1.499 | -0.393 | -2.532 |

| VARIABLES | (8)<br>Down<br>interaction | (9)<br>Up<br>placebo | (10)<br>Down<br>placebo | (11)<br>Up<br>placebo<br>interaction | (12)<br>Down<br>placebo<br>interaction |
|---|---|---|---|---|---|
| foreign_exp | 8.901 | 3.755 | 2.318 | -4.828 | -7.013 |
| | (8.344) | (11.89) | (13.18) | (4.717) | (4.563) |
| foreign_exp * tradability | -174.5** | | | 51.45 | 31.64 |
| | (76.28) | | | (53.43) | (57.97) |
| Observations | 1,084 | 1,084 | 1,084 | 1,084 | 1,084 |
| FE | s | s | s | s | s |
| Cluster | n | n | n | n | n |
| | -0.0169 | 0.00937 | 0.00614 | 0.00263 | -0.00771 |
| | -1.166 | 0.552 | 0.430 | 0.137 | -0.540 |
| | -0.0169 | 0.00937 | 0.00614 | 0.00263 | -0.00771 |
| | -1.166 | 0.552 | 0.430 | 0.137 | -0.540 |

Robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

This table shows the association between home-country residual P/E ratio and upstream and downstream exposures to foreign climate risks. Column 1 and 2 show the impact of upstream and downstream foreign climate risk exposures for all sectors. Column 3 and 5 show the impact of upstream and downstream foreign climate risk exposures on the residual P/E ratio of the industrial producers sector. Column 4 and 6 show the impact of upstream and downstream foreign climate risk exposures on the residual P/E ratio of the real estate sector. Column 7 and 8 adds to Column 1 and 2, respectively, the interaction between upstream and downstream foreign climate risk exposures and the importing and exporting tradability. Column 9 and 10 present the result with placebo upstream and downstream foreign exposures–openness to trade. Column 11 and 12 add the inteaction between openness to trade and importing and exporting tradability. In columns 1–6 and 9–10, row $\Delta sd$ refers to the change in standard error of the dependent variable associated with one standard deviation increase in the independent variable. In columns 7–8 and 11–12, row $\Delta sd$ refers to the change in standard error of the dependent variable associated with one standard deviation increase in the exposure to foreign climate risks, for sectors with median tradability. In Columns 1–6 and 9–10, row $\Delta interq$ refers to the change in the magnitude of the dependent variable associated with increasing the independent variable from its 25th percentile to 75th percentile. In Columns 7–8 and 11–12, row $\Delta interq$ refers to the change in the magnitude of the dependent variable associated with increasing the independent variable from its 25th percentile to 75th percentile, for sectors with median tradability.

the downstream exposures):[46]

$$RPE_i^s = b\, U_i \; + \; c\, TDIM^s * U_i + \zeta^s + \epsilon_i^s$$

We control for the sector fixed effect. Columns 7–8 of Table 4 show the results. Once the interaction term is introduced, the level effects of upstream and downstream foreign climate risks become insignificant. This indicates that the tradable sectors drive the negative association between foreign climate risk exposures and home-country P/E ratios for the average sector. For the sector at the 50th percentile of importing tradability (food and beverages), a one standard deviation increase in exposures to upstream foreign risks is associated with a 0.0488 standard deviation decline in the P/E ratio. For the sector with the 25th percentile importing tradability (travel and leisure), the number is 0.0286. For the sector with the 75th percentile importing tradability (industrial producers), the number is 0.0742. A one standard deviation increase in the downstream foreign risk exposures is associated with a 0.0075, a 0.0169, and a 0.1066 standard deviation decline for the sector at the 25th (insurance), the 50th (media), and the 75th (industrial producers) percentiles of exporting tradability, respectively.

The foreign climate risk exposure measures are a weighted sum of foreign trade shares and foreign climate risks. Therefore, if we hold fixed the foreign climate risks, openness to trade with all foreign countries can increase the foreign climate risk exposures, making it a confounding factor. We use a robustness test to show that the negative association between the P/E ratios and foreign exposures is not solely driven by openness to trade. We construct placebo upstream and downstream foreign risks by setting the placebo climate risks of all countries to $\frac{1}{N-1}$. A country's placebo upstream foreign climate risks then equal the following:

$$\widetilde{U}_n = \frac{1}{N-1} \sum_{i \neq n} S_{ni}$$

$\widetilde{U}_n$ denotes the average output share by all foreign countries to country $n$. A larger $\widetilde{U}_n$ means country $n$ is more important as a global exporting destination. A country's placebo downstream foreign climate risks equal the following:

$$\widetilde{D}_i = \frac{1}{N-1} \sum_{n \neq i} \pi_{ni}$$

[46] We also run a similar regression by replacing the country-level upstream foreign climate risks with a country fixed effect. The estimated coefficient before the interaction term is similar across the two regressions. We stick to the current specification because we would like to compare the result to the level regression before. The current specification also helps us interpret the magnitude of the coefficients.

$\widetilde{D}_i$ denotes the average expenditure share by all foreign countries on country $i$. A larger $\widetilde{D}_i$ means country $i$ is more important as a global importing origin.

The robustness tests concern the following regressions (for the regressions on downstream exposures, just replace $\widetilde{U}_{i,t}$ with $\widetilde{D}_i$ and $TDIM^s$ with $TDEX^s$):

$$RPE_i^s = \widetilde{b} * \widetilde{U}_i + \zeta^s + \epsilon_i^s$$

$$RPE_i^s = \widetilde{b} * \widetilde{U}_i + \widetilde{c}\, TDIM^s * \widetilde{U}_i + \zeta^s + \epsilon_i^s$$

Columns 9–10 of Table 4 show that the placebo foreign exposures are not significantly correlated with the P/E ratios in the home country. If anything, the correlation is weakly positive. Columns 11–12 find that the interaction between the placebo foreign exposures and the tradability measures is not significantly correlated with the P/E ratios in the home country. This shows that openness to trade alone cannot explain the negative association between the home-country P/E ratios and exposures to foreign climate risks. Instead, the key driver for the negative correlation is trading with the countries that have high climate risk exposures.

Furthermore, we show that the association between home-country stock valuations and exposures to foreign climate risks is not driven by openness to trade with bigger, richer countries and the countries that have stronger current economic growth. One might be wondering whether these countries happen to be those that have low climate risks, and trading with these countries may lead to stronger future growth of countries and sectors. To rule out these confounding channels, we replace climate risks $R_i$ in Equations 2 and 3 with current values of GDP, GDP per capita, GDP growth and GDP per capita growth of respective countries. In Appendix Table A.6, we show that none of these variables is significantly correlated with the residual P/E ratio at home. Compared to nontradable sectors, the tradable sectors' stock valuations do not benefit significantly more from openness to trade with these countries, either. This shows that none of these confounding variables has significant explanatory power for home-country stock valuation after we control for the standard predictors of future stock price.

In sum, in this section, we find significant correlation between exposures to foreign climate change risk and domestic stock valuations for tradable sectors, but the magnitude is economically small. We do not find strong such correlation for non-tradable sectors. This result suggests that climate change risk in trade partner countries has not become a major factor in asset valuations at home. However, as in the previous sections, we find that the effect of foreign climate disasters can be significant for tradable sector stock prices at home. As investors gradually incorporate foreign climate risks into domestic asset prices, even a country that is not subject to high degrees of climate change risks at home could experience domestic price corrections (especially in tradable sectors) because of trade linkages.

## 7 Conclusion

Climate change presents a major challenge to the economic wellbeing of many countries, and the economic effect of climate disasters can be extremely devastating. Building resilience against climate shocks is important to enhancing macrofinancial stability. However, there is also a global aspect to climate risk: international trade and supply chain linkages can propagate climate risks across country borders. A climate disaster that happens to any part of the sophisticated and interconnected global supply chain can have significant macrofinancial implications on other countries that share the same network.

In this paper, we find consistent evidence that climate disasters can have negative effects on the asset returns of the aggregate market and tradable sectors in major trade partner countries. Exposures to foreign long-term climate change risks also reduce the asset price valuations of the tradable sectors at home. The financial stability implications of these effects depend on many country-specific factors, such as the size of tradable sectors to the overall economy and the exposure of domestic banks to tradable sectors.[47] These results indicate that enhancing resilience against climate risk through adaptation efforts benefits the economic well-being of all countries. Many emerging market and developing economies are vulnerable to climate change. Yet they play an important role in the modern global value chain. Therefore, advanced economies should have the incentives to support emerging market and developing economies to adapt to climate change. We call for international collaboration and collective policy actions.[48]

While this paper focuses on the physical climate risk, the conceptual framework and analytical method could be applied to understand the transition risk and decarbonization efforts in response to climate change as well. The framework is also readily applicable to the cross-border spillovers of other crises, for example, COVID-19, among oth-

[47] Quantifying the effect on individual countries' financial stability requires general equilibrium analysis and model parameters calibrated to each country, which we will leave to future research.

[48] Some small island countries (for example, the Pacific and Caribbean island countries) might benefit less from foreign climate change adaptation efforts because they have not been fully integrated into the global value chain. An important factor of their segregation from the rest of the world is simply that they are the most vulnerable to climate disasters and climate risks. To gain from these countries' economic potentials, the world should collaborate to help them adapt to climate change.

ers. The methodology may also be extended to study the spillovers of shocks with other means of globalization, for example, multinational production, remittance, tourism, and so on. We also note that other global supply chain characteristics, such as input-specificity, could also significantly affect the disaster transmission channel and that further empirical tests could be conducted using more granular data. While the current project studies the spillovers of climate shocks across country borders, the same techniques could be applied to a more regional setting, to firm-to-firm trade and within-firm trade as well. While the paper focuses on the asset price implications, more works could be done for the impact on the real economy, for example, the labor market, and so on. Going forward, we anticipate more academic and policy research to examine the role of the constantly evolving global supply chain in determining the cross-border implications of climate change. Lastly, the analysis on differential P/E ratios could alternatively be used to back out the different levels of implied costs of capital across countries that are associated with climate risk. This methodology could be further used to evaluate and quantify the costs and benefits of infrastructure investments that enhance climate resilience.

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# A Data appendix

## A.1 Variable construction

We obtain information on country-bilateral total trade for the same set of countries and years from the United Nations Comtrade Database. We acquire countries' annual GDP data, $VA_{i,y}$, from the United Nations National Account Database. We get the value added to gross output ratio ($VAS_{i,y}$) from the international input-output database constructed by Johnson and Noguera (2017) and the OECD Analytical Activity of Multinational Enterprises database (henceforth OECD AAMNE, see Cadestin et al. 2018). With these we compute the expenditure shares, $\pi_{ni,y}$, and the output shares, $S_{ni,y}$. Detailed procedures to construct the expenditure shares, $\pi_{ni,y}$, and the output shares, $S_{ni,y}$, are presented in Appendix Section A.1

## A.2 Measuring the contribution by globalization to the decline in cross-country dispersion of global climate risks exposures

An alternative means of understanding globalization's contribution is to investigate the fraction of the reduction in cross-country dispersion in climate shock exposures that could be explained by variations in trade shares and variations in climate shocks.[49] Define the contribution by climate shocks alone (using the upstream exposures as an example) as the following:

$$Contribution\_climate = \frac{sd\_n\left(U_{n,y_0,y}\right) - sd\_n\left(U_{n,y_0,y_0}\right)}{sd\_n\left(U_{n,y,y}\right) - sd\_n\left(U_{n,y_0,y_0}\right)}$$

The numerator measures the difference between 1) the cross-country dispersion in climate risk exposure computed with the climate shocks in $y = 2018$ and the trade shares in $y_0 = 1971$ and 2) the same variable computed with both the climate shocks and trade shares in $y_0 = 1971$. The denominator measures the difference between 1) the cross-country dispersion in climate risk exposure computed with both the climate shocks and the trade shares in $y = 2018$ and 2) the same variable computed with both the climate shocks and trade shares in $y_0 = 1971$. Similarly, define the contribution by openness to trade alone as follows, where the numerator measures the difference between 1) the cross-country dispersion in climate risk exposure computed with the climate shocks in

[49] Note that due to their correlations, the contribution by climate shocks alone and the contribution by openness to trade alone may not add up to 1.

$y_0 = 1971$ and the trade shares in $y = 2018$ and 2) the same variable computed with both the climate shocks and trade shares in $y_0 = 1971$. The denominator is the same as measuring the contribution by climate:

$$Contribution\_trade = \frac{sd_n\left(U_{n,y,y_0}\right) - sd_n\left(U_{n,y_0,y_0}\right)}{sd_n\left(U_{n,y,y}\right) - sd_n\left(U_{n,y_0,y_0}\right)}$$

Applying the formula to the data shows that openness to trade alone explains 87.4 percent and 83.7 percent of the decline in cross-country dispersion of upstream and downstream exposures to global climate disasters, respectively. Conversely, changes in the geographical distribution of climate disasters alone explain 35.9 percent and 29.7 percent of the decline in cross-country dispersion of upstream and downstream exposures, respectively. These results re-emphasize that openness to trade explains the decline in cross-country differences in global climate shock exposures more than simply changes in the spatial distribution of climate shocks.

## A.3 Additional tables

Table A.1: Sample economies

| Advanced Economies | | | | Emerging Market and Developing Economies | | | |
|---|---|---|---|---|---|---|---|
| Sample | Johnson and Noguera | WIOD | OECD AAMNE | Sample | Johnson and Noguera | WIOD | OECD AAMNE |
| AUS | 1 | 1 | 1 | ARE | 0 | 0 | 0 |
| AUT | 1 | 1 | 1 | ARG | 1 | 0 | 1 |
| BEL | 1 | 1 | 1 | BGR | 0 | 1 | 1 |
| CAN | 1 | 1 | 1 | BHR | 0 | 0 | 0 |
| CHE | 1 | 0 | 1 | BRA | 1 | 1 | 1 |
| CYP | 0 | 1 | 1 | CHL | 1 | 0 | 1 |
| CZE | 1 | 1 | 1 | CHN | 1 | 1 | 1 |
| DEU | 1 | 1 | 1 | COL | 0 | 0 | 1 |
| DNK | 1 | 1 | 1 | EGY | 0 | 0 | 0 |
| ESP | 1 | 1 | 1 | HRV | 0 | 0 | 0 |
| EST | 1 | 1 | 1 | HUN | 1 | 1 | 0 |
| FIN | 1 | 1 | 1 | IDN | 1 | 1 | 0 |
| FRA | 1 | 1 | 1 | IND | 1 | 1 | 0 |
| GBR | 1 | 1 | 1 | JOR | 0 | 0 | 0 |
| GRC | 1 | 1 | 1 | KWT | 0 | 0 | 0 |
| HKG | 0 | 0 | 1 | LKA | 0 | 0 | 0 |
| IRL | 1 | 1 | 1 | MAR | 0 | 0 | 1 |
| ISR | 1 | 0 | 1 | MEX | 1 | 1 | 1 |
| ITA | 1 | 1 | 1 | MYS | 0 | 0 | 1 |
| JPN | 1 | 1 | 1 | NGA | 0 | 0 | 0 |
| KOR | 1 | 1 | 1 | OMN | 0 | 0 | 0 |
| LTU | 0 | 1 | 1 | PAK | 0 | 0 | 0 |
| LUX | 0 | 1 | 1 | PER | 0 | 0 | 0 |
| MLT | 0 | 1 | 1 | PHL | 0 | 0 | 1 |
| NLD | 1 | 1 | 1 | POL | 1 | 1 | 1 |
| NOR | 1 | 0 | 1 | QAT | 0 | 0 | 0 |
| NZL | 1 | 0 | 1 | ROU | 1 | 1 | 1 |
| PRT | 1 | 1 | 1 | RUS | 1 | 1 | 1 |
| SGP | 0 | 0 | 1 | SAU | 0 | 0 | 1 |
| SVK | 1 | 1 | 1 | THA | 1 | 0 | 1 |
| SVN | 1 | 1 | 1 | TUR | 1 | 1 | 1 |
| SWE | 1 | 1 | 1 | VEN | 0 | 0 | 0 |
| TWN | 0 | 1 | 1 | VNM | 1 | 0 | 1 |
| USA | 1 | 1 | 1 | ZAF | 1 | 0 | 1 |

This table shows the sample economies and whether these economies are included in the international input-output databases that we use, including Johnson and Noguera (2017), the WIOD 2016 release (Timmer et al., 2015), and the OECD AAMNE (Cadestin et al., 2018). A "1" means that the economy is included in the database indicated in the column header. A "0" means that the economy is not included.

Table A.2: Concordance between the Datastream sectors and the aggregate sectors

| Datastream sectors | Datastream sector names | Aggregate sectors |
|---|---|---|
| MRKTS | market | MRKTS |
| AUTMB | automobiles and parts | AUTMB |
| BANKS | banks | FINSV |
| BMATR | basic materials | BMATR |
| BRESR | basic resources | BRESR |
| CHMCL | chemicals | CHMCL |
| CNSTM | construction and materials | CNSTM |
| FDBEV | food and beverages | FDBEV |
| FINSV | financial services | FINSV |
| FOODS | food producers | FDBEV |
| HHOLD | household goods and home construction | HHOLD |
| HLTHC | healthcare | HLTHC |
| INDGS | industrial goods | INDUS |
| INDUS | industrial producers | INDUS |
| INSUR | insurance | INSUR |
| LFINS | life insurance | INSUR |
| MEDIA | media and communication sector | MEDIA |
| NLINS | non-life insurance | INSUR |
| PCINS | property and casualty insurance | INSUR |
| REINS | reinsurance | INSUR |
| RLEST | real estate | RLEST |
| RTAIL | retail | RTAIL |
| TECNO | technology | TECNO |
| TELCM | telecommunications | TELCM |
| TRLES | travel and leisure | TRLES |
| UTILS | utilities | UTILS |

Table A.3: Concordance between the WIOD 2016 release sectors and the aggregate sectors

| WIOD sector num | WIOD sectors | Aggregate sectors | WIOD sector num | WIOD sectors | Aggregate sectors |
|---|---|---|---|---|---|
| 1 | A01 | FDBEV | 29 | G46 | RTAIL |
| 2 | A02 | BRESR | 30 | G47 | RTAIL |
| 3 | A03 | FDBEV | 31 | H49 | INDUS |
| 4 | B | BRESR | 32 | H50 | INDUS |
| 5 | C10-C12 | FDBEV | 33 | H51 | INDUS |
| 6 | C13-C15 | HHOLD | 34 | H52 | INDUS |
| 7 | C16 | BRESR | 35 | H53 | INDUS |
| 8 | C17 | BRESR | 36 | I | TRLES |
| 9 | C18 | MEDIA | 37 | J58 | MEDIA |
| 10 | C19 | CHMCL | 38 | J59_J60 | MEDIA |
| 11 | C20 | CHMCL | 39 | J61 | TELCM |
| 12 | C21 | HLTHC | 40 | J62_J63 | TECNO |
| 13 | C22 | CHMCL | 41 | K64 | FINSV |
| 14 | C23 | BMATR | 42 | K65 | INSUR |
| 15 | C24 | BMATR | 43 | K66 | FINSV |
| 16 | C25 | BMATR | 44 | L68 | RLEST |
| 17 | C26 | INDUS | 45 | M69_M70 | Other |
| 18 | C27 | INDUS | 46 | M71 | TECNO |
| 19 | C28 | INDUS | 47 | M72 | TECNO |
| 20 | C29 | AUTMB | 48 | M73 | TECNO |
| 21 | C30 | AUTMB | 49 | M74_M75 | TECNO |
| 22 | C31_C32 | HHOLD | 50 | N | Other |
| 23 | C33 | AUTMB | 51 | O84 | Other |
| 24 | D35 | UTILS | 52 | P85 | Other |
| 25 | E36 | UTILS | 53 | Q | Other |
| 26 | E37-E39 | UTILS | 54 | R_S | Other |
| 27 | F | CNSTM | 55 | T | Other |
| 28 | G45 | RTAIL | 56 | U | Other |

The WIOD 2016 release (Timmer et al., 2015) sectors are based on ISIC Rev. 4 classifications.

Table A.4: Summary statistics

| Variable | N | Mean | Sd | 1% | 5% | 25% |
|---|---|---|---|---|---|---|
| Damage (current k$) | 5324 | 7.83E+05 | 4.01E+06 | 5.00E+01 | 8.55E+02 | 1.30E+04 |
| Death | 5324 | 113 | 971 | 0 | 0 | 2 |
| Affected | 5324 | 1.36E+06 | 1.04E+07 | 0.00E+00 | 0.00E+00 | 2.40E+01 |
| Damage to home-country GDP | 5324 | 9.14E-04 | 4.06E-03 | 1.47E-07 | 1.31E-06 | 1.96E-05 |
| $S_{n_D i(d),y(d)}$ | 5324 | 0.0313 | 0.0315 | 0.0036 | 0.0068 | 0.0107 |
| $\pi_{n(d),i_U y(d)}$ | 5324 | 0.0274 | 0.0273 | 0.0037 | 0.0061 | 0.0121 |
| nor_up_damage | 5324 | 1.23E-05 | 1.16E-04 | 4.02E-10 | 3.40E-09 | 7.58E-08 |
| nor_down_damage | 5324 | 1.29E-05 | 7.45E-05 | 4.31E-10 | 3.29E-09 | 8.92E-08 |
| $CAR^{mkt}$ | 4960 | -0.0047 | 0.0605 | -0.1965 | -0.1012 | -0.0334 |
| TDIM | 20 | 0.1804 | 0.1536 | 0.0123 | 0.0311 | 0.0624 |
| TDEX | 20 | 0.3181 | 0.3250 | 0.0027 | 0.0091 | 0.0830 |
| factoring_to_gdp (%) | 712 | 2.9 | 3.7 | 0.0 | 0.1 | 0.5 |
| regulatory_to_assets (%) | 651 | 14.4 | 3.6 | 8.2 | 10.3 | 12.2 |
| $R_i$ | 57 | 0.0108 | 1.0400 | -1.4100 | -1.4000 | -0.6818 |
| $U_i$ | 57 | -0.0055 | 0.1443 | -0.5753 | -0.1802 | -0.0537 |
| $D_i$ | 57 | -0.0166 | 0.1312 | -0.6636 | -0.1825 | -0.0634 |
| $RPE_i^{mkt}$ | 57 | -0.7805 | 3.7447 | -8.5697 | -6.4680 | -2.7556 |

| Variable | 50% | 75% | 95% | 99% |
|---|---|---|---|---|
| Damage (current k$) | 1.00E+05 | 4.50E+05 | 2.91E+06 | 1.16E+07 |
| death | 11 | 41 | 283 | 1399 |
| affected | 4.67E+03 | 1.05E+05 | 3.27E+06 | 2.46E+07 |
| Damage to home-country GDP | 1.04E-04 | 4.90E-04 | 3.75E-03 | 1.17E-02 |
| $S_{n_D i(d),y(d)}$ | 0.0188 | 0.0397 | 0.0981 | 0.1373 |
| $\pi_{n(d),i_U y(d)}$ | 0.0178 | 0.0318 | 0.0854 | 0.1171 |
| nor_up_damage | 4.50E-07 | 2.73E-06 | 3.04E-05 | 2.06E-04 |
| nor_down_damage | 6.74E-07 | 3.98E-06 | 4.69E-05 | 2.22E-04 |
| $CAR^{mkt}$ | -0.0029 | 0.0255 | 0.0903 | 0.1438 |
| TDIM | 0.1346 | 0.2555 | 0.5310 | 0.6004 |
| TDEX | 0.1436 | 0.5651 | 0.9694 | 1.0251 |
| factoring_to_gdp (%) | 1.4 | 4.0 | 10.4 | 13.8 |
| regulatory_to_assets (%) | 13.6 | 16.2 | 20.3 | 25.1 |
| $R_i$ | -0.2473 | 0.5402 | 1.9998 | 2.1949 |
| $U_i$ | -0.0014 | 0.0164 | 0.2104 | 0.5777 |
| $D_i$ | -0.0002 | 0.0214 | 0.1922 | 0.2920 |
| $RPE_i^{mkt}$ | -1.0041 | 1.7640 | 6.6599 | 7.7028 |

All variables are winsorized at top and bottom 1 percent to reduce the impact of the outliers on the results. Observations for variables damage, death, affected, damage to home-country GDP, nor_up_damage, nor_down_damage, and $CAR^{mkt}$ (defined in Equations 1, **??** and **??**) are on the climate disaster level. Observations for TDIM and TDEX are on the aggregate sector level. Observations for the factoring-to-GDP ratio and the bank regulatory capital-to-risk-weighted assets ratio are on the country-year level. Observations for $R_i$, $U_i$, $D_i$, and $RPE_i^{mkt}$ (defined in Equations 2, 3 and 4) are on the country level.

Table A.5: Cross-sectional analysis: association between country institutional factors and cumulative abnormal return in the financial sector

| VARIABLES | (1)<br>CAR40 | (2)<br>CAR40 | (3)<br>CAR40 | (4)<br>CAR40 |
|---|---|---|---|---|
| nor_up_damage | -57.00 | -148.7 | | |
| | (210.3) | (241.6) | | |
| nor_down_damage | | | -9.707 | -24.59 |
| | | | (18.68) | (22.60) |
| factoring_to_gdp (%) | 0.00108** | | 0.00105** | |
| | (0.000373) | | (0.000406) | |
| regulatory_to_assets (%) | | 0.00213*** | | 0.00250* |
| | | (0.000559) | | (0.00141) |
| | | | | |
| Observations | 6,531 | 5,611 | 5,345 | 4,377 |
| Cluster | n; y | n; y | n; y | n; y |

Robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

This table shows the association between country institutional factors and trading day 40's (from 21 trading days before the disaster to 40 trading days after the disaster) cumulative abnormal return from a foreign climate disaster in the financial sector. The financial sector refers to the banking sector and other financial services (asset managers, consumer finance, specialty finance, investment services, and mortgage finance). The institutional factors include total factoring volume-to-GDP (%), as well as bank regulatory capital-to-risk-weighted assets (%). Column 1 regresses trading day 40's cumulative abnormal returns in the financial sector on normalized upstream damage and one-year lag of total factoring volume-to-GDP. Column 2 regresses trading day 40's cumulative abnormal return in the financial sector on normalized upstream damage and one-year lag of bank regulatory capital-to-risk-weighted assets ratio. Column 3 regresses trading day 40's cumulative abnormal return in the financial sector on normalized downstream damage and one-year lag of the total factoring volume-to-GDP. Column 4 regresses trading day 40's cumulative abnormal return in the financial sector on normalized downstream damage and one-year lag of bank regulatory capital-to-risk-weighted assets ratio. Standard errors are two-way clustered on the stock market and year level.

Table A.6: Association between placebo exposure measures and home-country P/E ratio

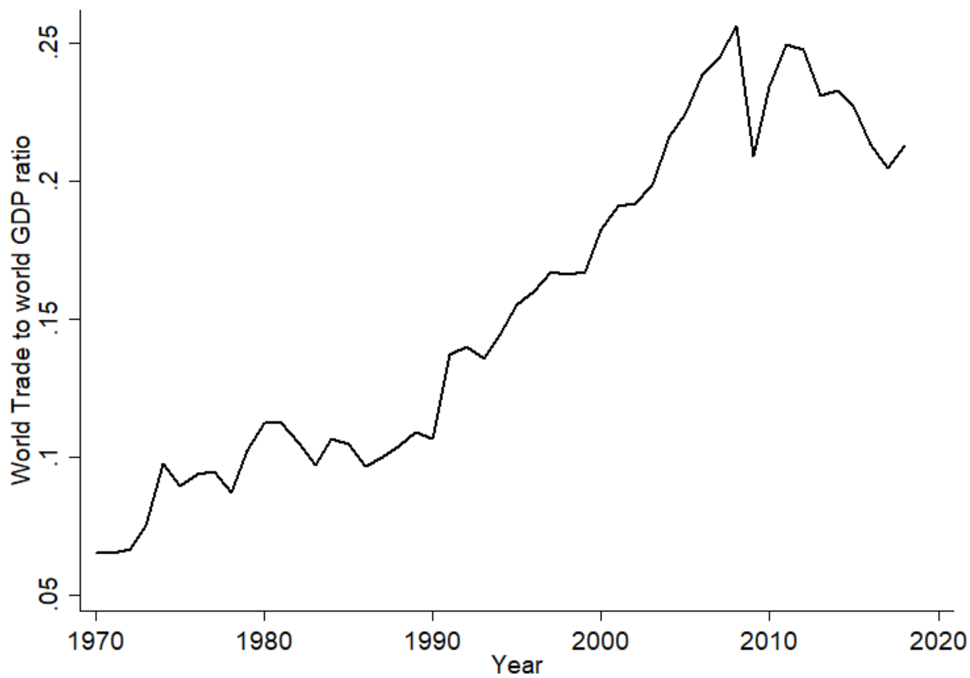
| VARIABLES | (1) Up GDP | (2) Up GDP per capita | (3) Up GDP growth | (4) Up GDP per capita growth | (5) Down GDP | (6) Down GDP per capita | (7) Down GDP growth | (8) Down GDP per capita growth |
|---|---|---|---|---|---|---|---|---|
| placebo foreign_exp | 0.138 | 0.424 | 66.81 | 94.89 | 0.0809 | 0.284 | 65.29 | 86.73 |
| | (0.445) | (1.200) | (153.8) | (165.7) | (0.496) | (1.323) | (165.3) | (177.4) |
| placebo foreign_exp * tradability | | | | | | | | |
| Observations | 1,084 | 1,084 | 1,084 | 1,084 | 1,084 | 1,084 | 1,084 | 1,084 |
| FE | s | s | s | s | s | s | s | s |
| Cluster | n | n | n | n | n | n | n | n |
| VARIABLES | (9) Up GDP | (10) Up GDP per capita | (11) Up GDP growth | (12) Up GDP per capita growth | (13) Down GDP | (14) Down GDP per capita | (15) Down GDP growth | (16) Down GDP per capita growth |
| placebo foreign_exp | -0.183 | -0.483 | -61.03 | -64.50 | -0.263 | -0.720 | -100.6* | -114.5* |
| | (0.176) | (0.478) | (62.20) | (66.98) | (0.172) | (0.452) | (53.97) | (56.98) |
| placebo foreign_exp * tradability | 1.922 | 5.433 | 763.2 | 950.1 | 1.165 | 3.398 | 558.1 | 675.1 |
| | (1.999) | (5.396) | (694.5) | (742.1) | (2.184) | (5.780) | (703.4) | (745.4) |
| Observations | 1,084 | 1,084 | 1,084 | 1,084 | 1,084 | 1,084 | 1,084 | 1,084 |
| FE | s | s | s | s | s | s | s | s |
| Cluster | n | n | n | n | n | n | n | n |

Robust standard error in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

This table shows the association between home-country residual P/E ratio and upstream and downstream placebo exposure measures. Column 1-8 consider exposures to foreign GDP, GDP per capita, GDP growth, and GDP per capita growth in the upstream and downstream. Column 9-16 add to Column 1-8 the interactions between these variables and the respective tradability measures.

# B Additional figures

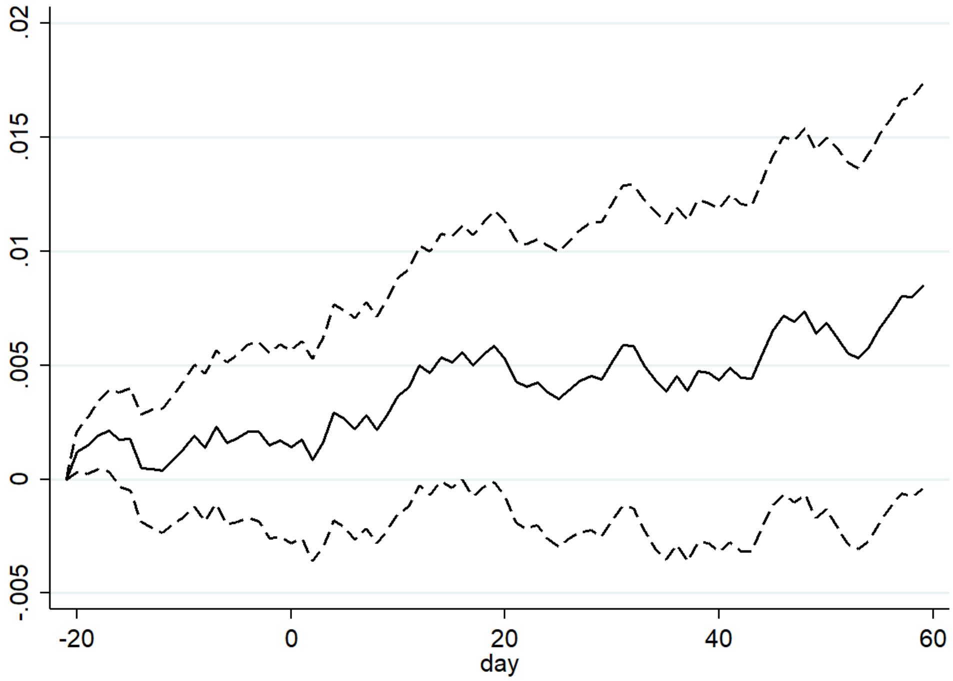
Figure B.1: World trade-to-world GDP ratio



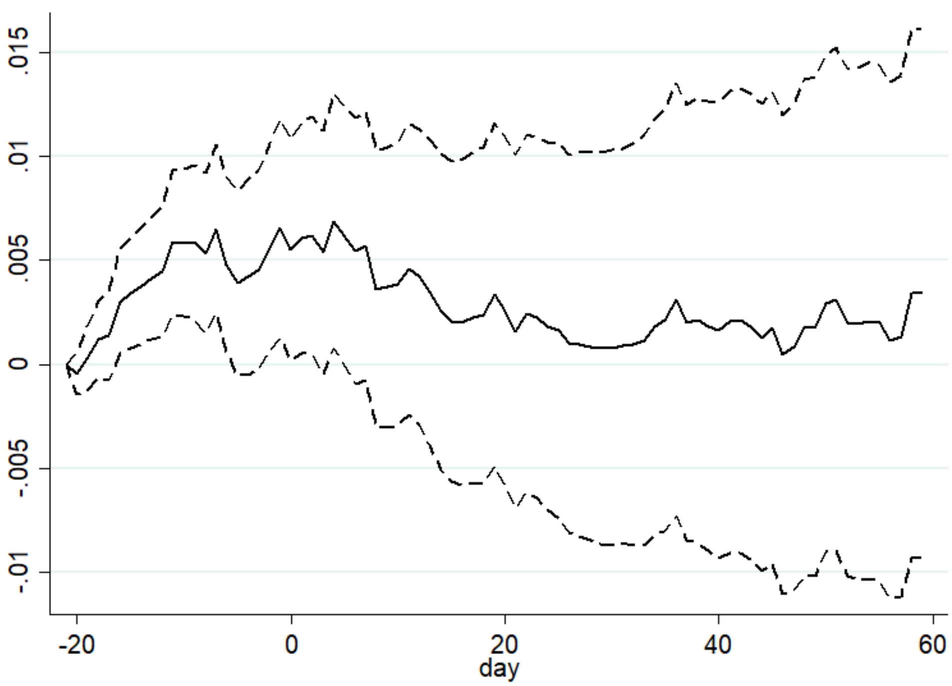

United Nations Comtrade Database and authors' construction. This figure plots the world trade-to-world GDP ratio from 1970 to 2018.

Figure B.2: Climate disasters do not significantly affect the stock market returns in non-major trade partners of the countries hit by climate disasters

(a) Placebo, upstream disaster



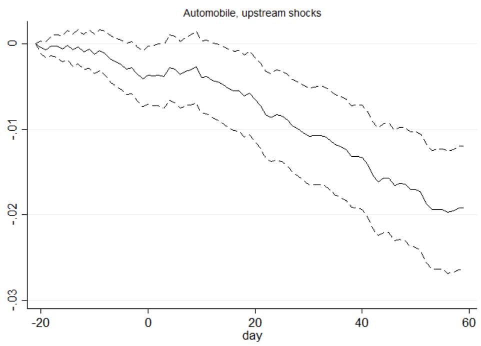

(b) Placebo, downstream disaster



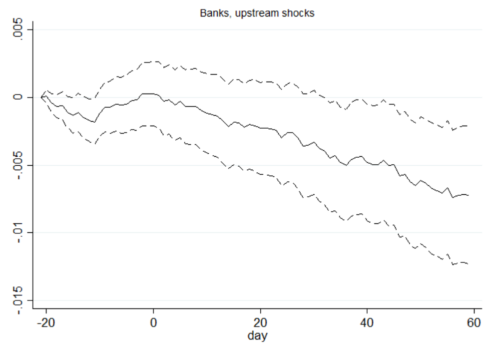

The figures plot the cumulative abnormal returns in the market indexes of the 35th largest exporting destination of the upstream disaster-hit country and the 35th largest importing origin of the downstream disaster-hit country from 20 days before the disaster to 60 days after the disaster.

Figure B.3: Sector-level stock market returns in the main exporting destination of upstream disaster-hit country

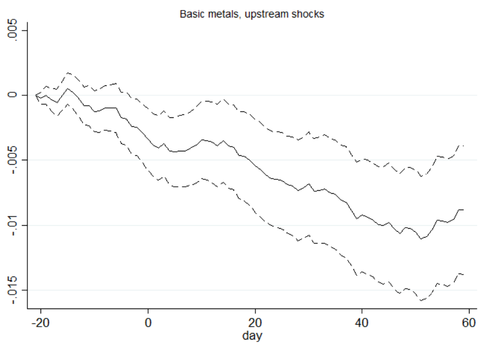
(a) Automobiles and parts



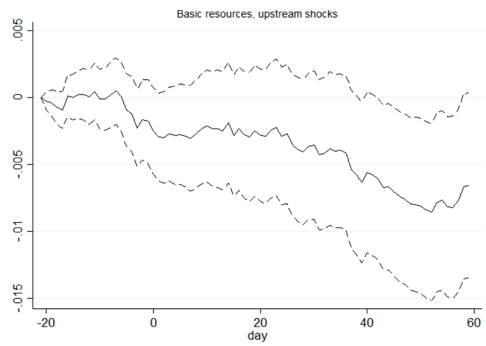

(b) Banks



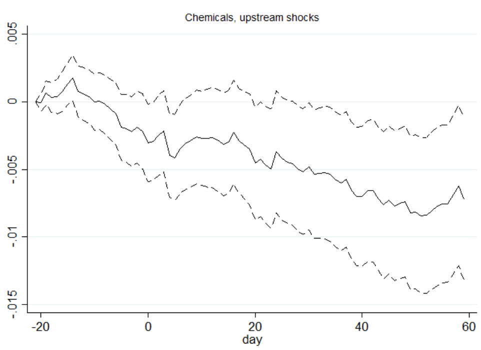

(c) Basic materials



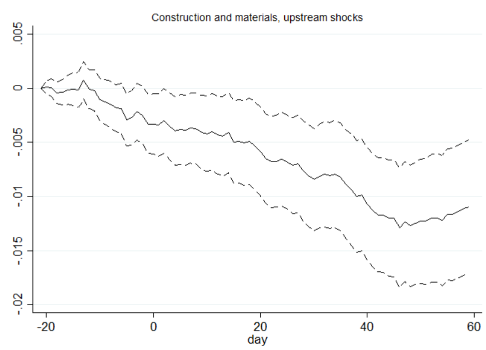

(d) Basic resources



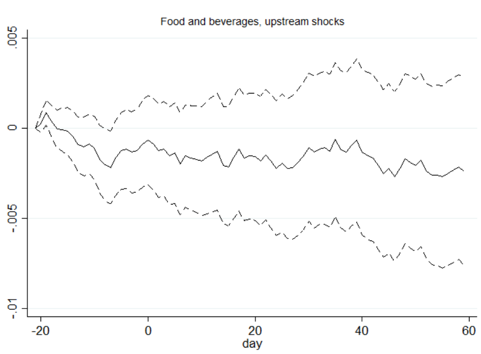

(e) Chemicals



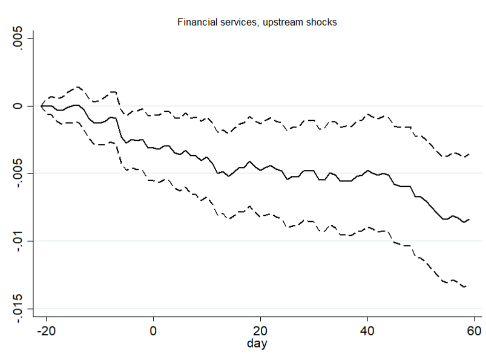

(f) Construction and materials



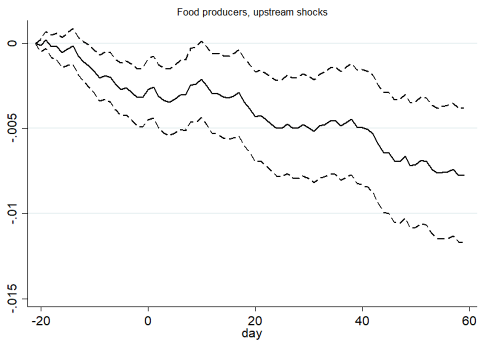

(g) Food and beverages




(h) Financial services



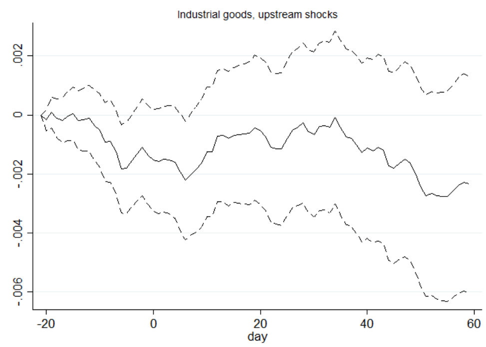
(i) Food producers




(j) Household goods and home construction

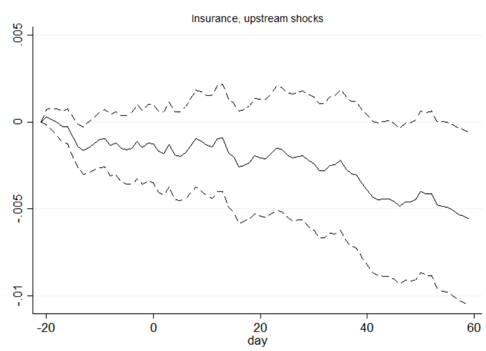

(k) Utilities


(l) Industrial goods

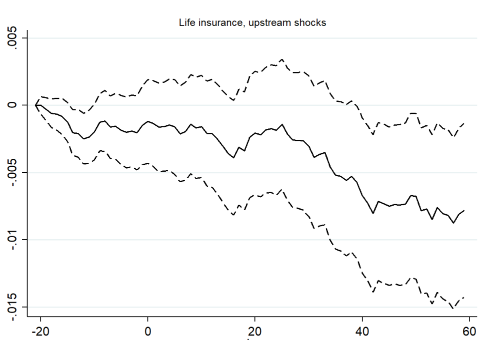



(m) Industrial producers

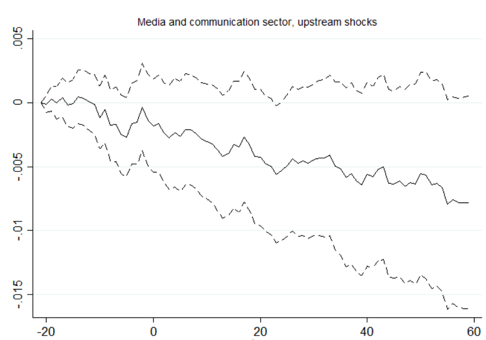

(n) Insurance



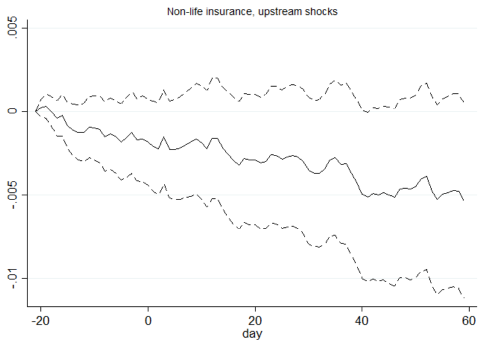

(o) Life insurance



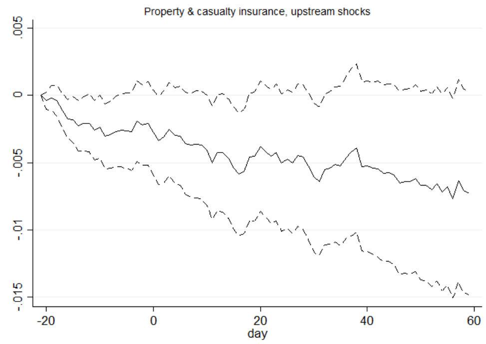

(p) Media and communication



(q) Non-life insurance



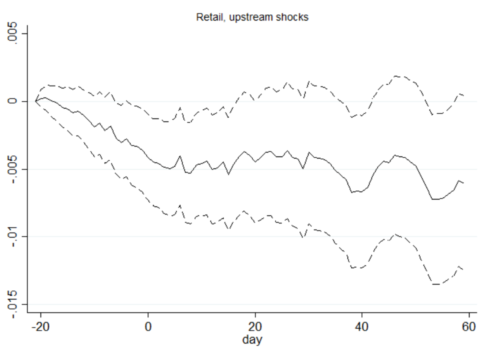

(r) Property and casualty insurance



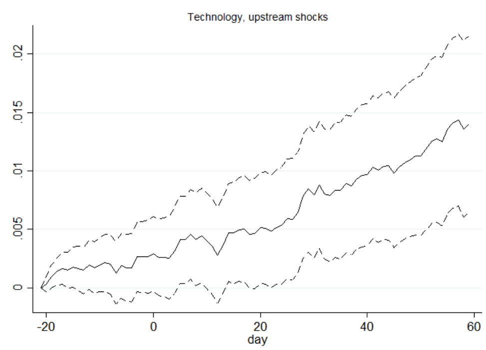

(s) Reinsurance


(t) Real estate

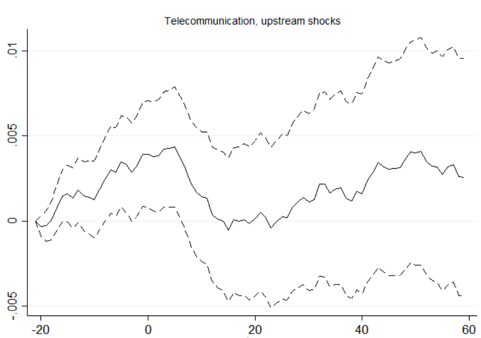

(u) Retail




(v) Technology




(w) Telecommunications

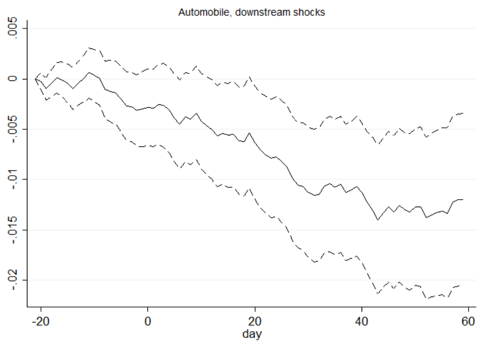



(x) Travel and leisure

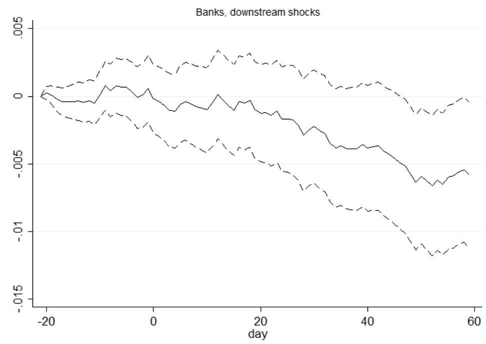

The figures plot cumulative abnormal returns in sector-level stock indexes in the main exporting destination of upstream disaster-hit country from 20 days before the upstream disaster to 60 days after the upstream disaster.

Figure B.4: Sector-level stock market returns in the main importing origin of downstream disaster-hit country

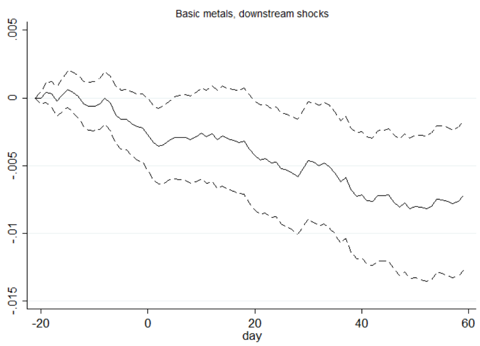
(a) Automobiles and parts




(b) Banks

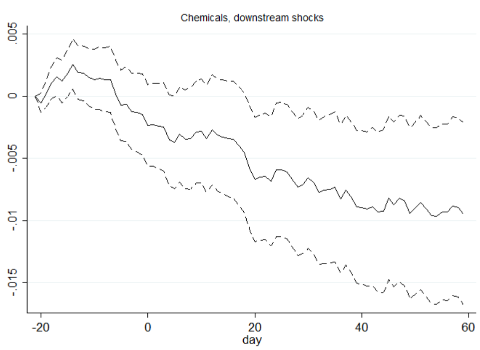



(c) Basic materials

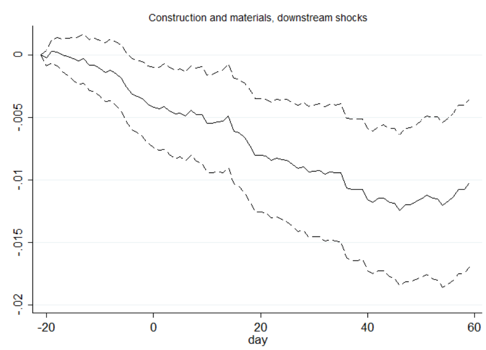



(d) Basic resources

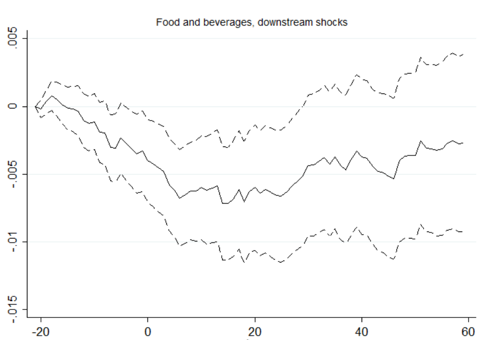

(e) Chemicals



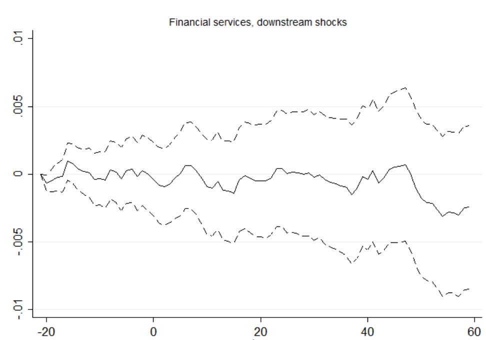

(f) Construction and materials



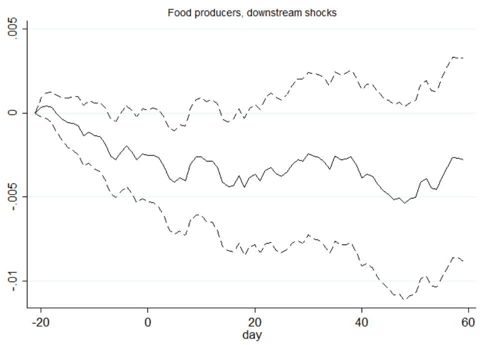

(g) Food and beverages



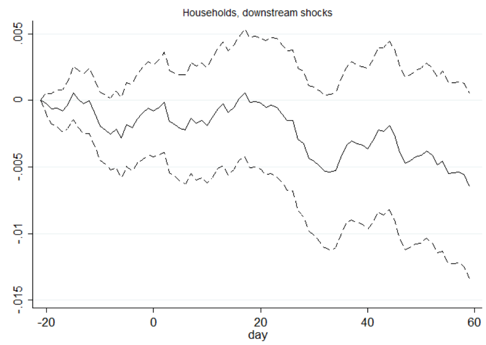

(h) Financial services



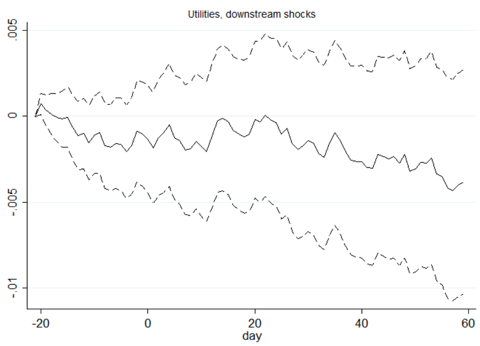
(i) Food producers




(j) Household goods and home construction



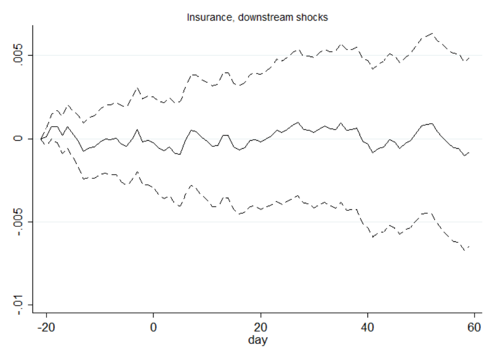

(k) Utilities



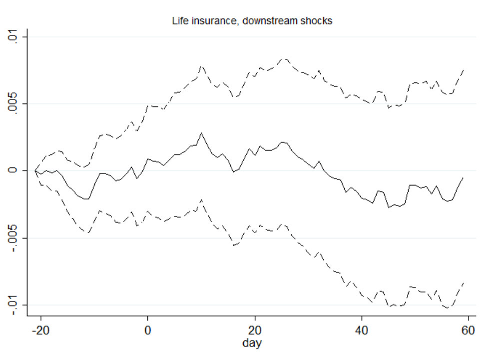

(l) Industrial goods


(m) Industrial producers

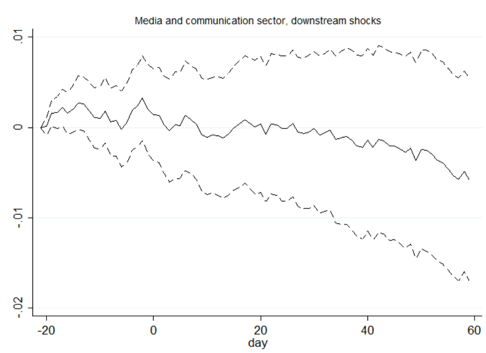

(n) Insurance



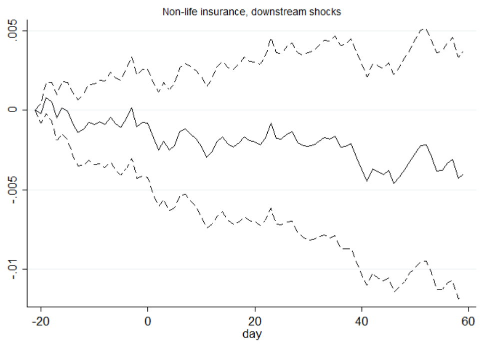

(o) Life insurance




(p) Media and communication

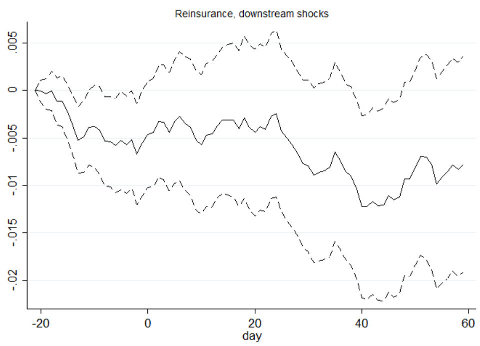


(q) Non-life insurance

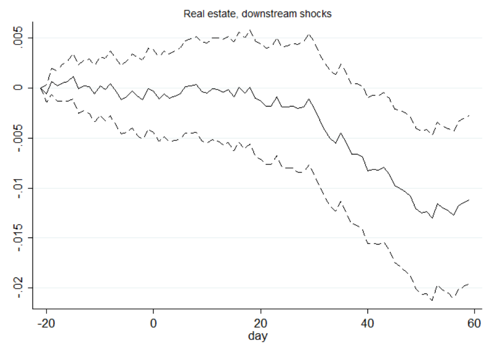



(r) Property and casualty insurance


(s) Reinsurance

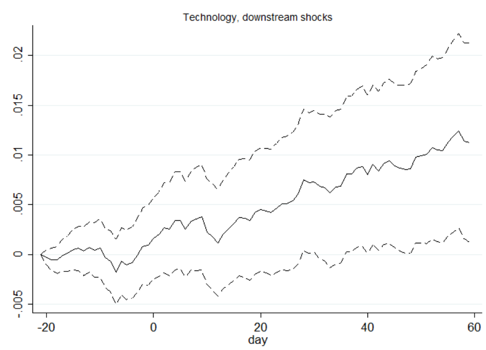



(t) Real estate

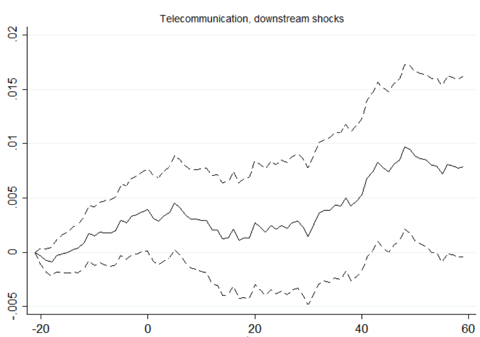



(u) Retail


(v) Technology




(w) Telecommunications




(x) Travel and leisure


The figures plot cumulative abnormal returns in sector-level stock indexes in the main importing origin of downstream disaster-hit country from 20 days before the downstream disaster to 60 days after the downstream disaster.