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

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February 9, 2023

Abstract

Are land locked countries subject to sea-level rise risk? We highlight a new mechanism by which physical climate shocks affects countries' macro-financial performance: the cross-border spillover effects that propagate through international trade. Basing our findings on historical data between 1970 and 2019, we find that climate disasters that hit the transport infrastructure – ports – decrease the affected country's imports and exports and reduce economic output in major trade partner (both upstream and downstream) countries. Climate disasters reduce stock market returns in the aggregate market and tradable sectors of the major trade partner countries. Exposures to foreign long-term climate change risks reduce the asset price valuations of the tradable sectors at home. Therefore, climate adaptation efforts in a country can have positive spillover effects on other countries' macro-financial performance and stability through international trade.

JEL classification: F42, G14, Q54

Keywords: climate risks, international trade, infrastructure, macro-financial stability

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1 Introduction

International collaboration 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 markets and developing economies require financing from advanced economies to adapt to climate change. They also rely on foreign advanced technologies so that they can transition to green production (Stavins et al., 2014).

However, the countries that have low climate risks at home may be unwilling to contribute to such collaboration. The distribution of climate risks is uneven across space.[1] Previous research finds that while many warm and poor countries may be severely hit by global warming, many cool and rich countries may not be harmed by higher temperatures. Rather, they may even benefit from a warmer globe (Diffenbaugh and Burke, 2019). Some argue that the latter group of countries, if they act in the best of their interests, may 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 argue that this gloomy view is partial, by asking the following question: Are disaster-free countries subject to foreign climate disaster risks? We highlight a new mechanism by which climate change affects countries' macro-financial performance: the cross-border spillover effects that propagate through international trade.

We are the first to provide the empirical evidence that shows a climate disaster, if it disrupts economic activities in any part of the global supply chain, can significantly affect the macroeconomic and financial performance of the affected country's main international trade partners. We start with constructing comprehensive datasets on global macroeconomic indicators, international trade, country-sector level stock market indices and valuation measures, climate disasters, transport infrastructure locations, and climate risks. We link each climate disaster with the country that is directly affected by the climate disaster, the country's main upstream and downstream trade partners defined with international trade shares, and determine whether the climate disaster hits a transport infrastructure that is critical for international trade – ports.[2]

To investigate the causal effect of climate disasters on the macro economy, we employ a matching-and-stacking difference-in-differences strategy. We match each country that

[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] In 2019, about 80% of the world's trade volume and more than 70% of the world's trade value were handled through ports (Sirimanne et al., 2019).

is hit by a climate disaster to a country that is otherwise similar but is not affected by a climate disaster. We match the main upstream and downstream countries of the affected country to the main upstream and downstream countries of the affected country's control.

We find that, first, a climate disaster that hits a port significantly reduces the affected country's total exports, exports to the main downstream country, total imports, imports from the main upstream country, and aggregate output. In an average month of the first four months after such a disaster hits, the disaster decreases the country's GDP by 0.45%, exports by 0.47%, and imports by 0.11%. However, a climate disaster that does not hit a port does not have such negative consequences on trade. Rather, it increases the affected country's imports.

Second, a climate disaster that hits a port significantly undermines the GDP of both the main upstream and downstream countries. In an average month after a disaster starts, the disaster reduces the main downstream country's GDP by 0.38% and the main upstream country's GDP by 0.35%. Climate disasters lead to supply chain restructuring: the affected country sells a lower share of output to the downstream country but spends a greater share of their expenditure on the upstream country. With a new formula that decomposes the total effect on main upstream and downstream GDP into a term that summarizes the demand/supply shock (fixing the trade shares) and another term that summarizes the trade disruptions, we find that export disruptions weakly decrease downstream GDP but the supply chain restructuring significantly alleviates the negative impact of climate disasters on upstream GDP. Climate disasters that do not hit ports do not significantly affect upstream and downstream countries' macroeconomic performance.

To study how climate disasters affect the stock market returns in the major trade partners, we use a financial market event study method. As stock market indices are available on the sector level, we can understand how climate disasters impact foreign economies not only on the aggregate level but also for individual sectors. We can also study these responses at higher frequencies.

We find that returns in both the aggregate stock market and tradable sector stocks in both the main upstream and downstream countries are negatively affected by climate disasters. From 20 trading days before a foreign climate disaster to 80 trading days after it, the aggregate stock market indices in these main trade partners fall by 0.5%. The impact on sectoral stock returns varies across sectors and is only significant for tradable sectors. For instance, in the automobile sector, the impact can be as high as -2% immediately following a foreign climate disaster. Using a cross-sectional analysis, we find that (1) exposures to foreign climate disasters (the size of the disaster's damage relative to downstream/upstream country's GDP and trade shares) and (2) sectoral tradability significantly increase the losses in sectoral stock returns from foreign climate disasters. Due to its importance for financial stability, we also examine the impact of foreign climate disasters on financial sectors. We find that financial sectors in countries that are less insured in international trade and have a more risky financial system are more affected by foreign climate disasters.

In the end, we find that exposures to foreign long-term climate change risks through international trade are also negatively associated with stock market valuations of tradable sectors at home. We measure the stock market valuation with the P/E ratio and the exposure to foreign climate change risk with country-level climate risk measures and the trade shares. We find that higher foreign climate change risk exposures are associated with lower P/E ratios in the aggregate market and tradable sectors at home. We show that these associations are not driven by openness to trade, trading with larger, wealthier countries or with the countries that grow faster.

We identify international trade as an important propagation mechanism of climate shocks in the following ways. First, we show that climate disasters that hit ports significantly reduce trade, but those that do not hit ports do not significantly affect exports but increase imports. Second, we show that whether climate disasters affect other transport infrastructure that is less important for international trade, for example, airports, does not affect the consequences in main trade partners. Third, we show that only in the tradable sectors the short-run stock market returns are affected by foreign climate disasters and the long-run stock market valuations are affected by foreign climate risks. Lastly, we also conduct placebo tests which show that climate disasters do not significantly affect the macro-financial performance in countries that trade little with the disaster-hit country.

With this paper, we contribute to the important policy discussions about climate change adaptation. We argue that optimal adaptation efforts require collective action in a multilateral framework. Helping other countries, especially major trade partners, to build the resilience against climate shocks also enhances the home country's climate resilience and improves domestic macro-financial performance. 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) that investigates the relationship between climate change and financial stability.[3] 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).

We contribute to the literature on the economic consequences of climate change. We

[3] See https://www.ngfs.net/en.

only present a brief survey of this literature.[4] The literature has found that climate disasters negatively impact a country's economic output, economic growth, physical and human capital, firm business performance, and especially so for low-income countries (Hsiang 2010, Dell et al. 2012, Burke et al. 2015, Somanathan et al. 2015, Kahn et al. 2019). Other works have found that extreme climate conditions undermine stock market earnings, returns, and prices. Therefore, they conclude that harsher climate harms financial stability in the affected country (Addoum et al. 2019, Hong et al. 2019, International Monetary Fund 2020).

We contribute to this literature in three ways. First, this literature has mostly focused on the impact on the local area or the country that faces climate disasters and climate risks directly, whereas we study the responses in the country's main foreign trade partners. Second, we demonstrate that international trade is an important propagation mechanism. We highlight that only the climate disasters that hit port infrastructure can disrupt trade and affect foreign output, and that only the tradable sectors are affected in the foreign country. Third, we present rich empirical evidence that shows not only that climate disasters affect short-run foreign output and stock returns, but also that climate risks are associated with long-run foreign stock market valuation declines.

The paper contributes to the international economics literature on the propagation of shocks across regions/sectors and business cycle synchronization. Empirical works in this literature (for example, Di Giovanni et al. 2018) have investigated how foreign economic shocks affect domestic firm performance. Quantitative works (for example, Backus et al. 1992, Caliendo et al. 2017, De Souza and Li 2020, Li 2021, Kleinman et al. 2021) simulate the impact of economic shocks that hit one region or sector on other parts of the economy.

We contribute to the empirical side of this literature by documenting empirical evidence of business cycle synchronization on the aggregate, country-sector level. We lend empirical support to the quantitative models in this literature. We highlight both the similarities and differences between climate shocks and traditional economic shocks. We show that similar to traditional productivity and demand shocks, climate shocks can also affect trade and thus propagate to a foreign country. Surveillance of foreign supply and demand shocks has been critical for a country's external sector stability.[5] We suggest that global governments and central banks should also monitor foreign climate shocks and take policy actions accordingly if such shocks happen. Unlike how shocks propagate in a domestic production input-output network where sectoral shares are generally taken

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

[5] See, for example, the annual external sector report of the International Monetary Fund: https://www.imf.org/en/Publications/SPROLLs/External-Sector-Reports.

as fixed (see, for example, Acemoglu et al. 2016), we show that climate shocks can lead to disruptions in trade, and such trade disruptions have asymmetric effects on upstream and downstream countries.

Additionally, we contribute to the nascent literature on the propagation of climate risks through trade and production. Some have investigated how disasters (climate and non-climate) affect the performance of foreign firms through international trade or multinational production linkages (Carvalho et al. 2016, Boehm et al. 2019, Dingel et al. 2019, Gu and Hale 2022), whereas others have studied the impact of climate disasters on domestic suppliers, customers, and labor migration (Barrot and Sauvagnat 2016, Balboni 2019). Other works build quantitative spatial models to study the macroeconomic consequences of climate change (Cruz et al. 2020 ,Conte et al. 2020, Conte 2022).[6]

We contribute to this literature in two ways. First, past empirical works in this literature have focused on the microeconomic supply chain impact of climate disasters on individual firms and households, whereas we provide new empirical strategies with which we demonstrate that climate shocks can have aggregate macro-financial implications in foreign economies. Second, in past quantitative works, these cross-border effects – a key input to compute the spatial and macroeconomic effects of climate change – are assumed to exist by the model. Their magnitudes are governed by the model's parameter assumptions. In this paper, we credibly test and identify the magnitudes of these cross-border spillover effects on the macro economy. The estimated coefficients help future modelers discipline their parameters.

The rest of the paper is organized as follows. In Section 2, we describe our data and variable construction. In Section 3, we introduce the difference-in-differences strategy with which we estimate the macroeconomic effects of climate disasters in the home country and main trade partners. In Section 4, we present the empirical findings for these macroeconomic effects. In Section 5, we investigate the impact of climate disasters on aggregate and sector-level stock market returns in the affected country's main trade partners. In Section 6, we study how exposures to foreign long-term climate change risks are associated with domestic stock market valuations. In Section 7, we conclude.

[6] This paper is also related to the literature on production networks, see, for example, Baqaee and Farhi (2019), Panigrahi (2021), Dhyne et al. (2021), among others.

2 Data and Variable Construction

We construct comprehensive datasets on global economies' macroeconomic indicators, international trade, country-sector level stock market indices and valuation measures, climate disasters, transport infrastructure locations, and climate risks. Our dataset covers 151 countries during half a century, from 1970 to 2019. Among these countries, 50 are advanced economies and the others are emerging markets and developing countries. Most data sources are described in the following subsections.

Macroeconomic Indicators To understand how climate disasters affect the macro economy in the countries that are directly affected and their main trade partners, we gather country-month level GDP, CPI, and consumption data. We start with quarterly and annual GDP data for countries from the International Financial Statistics (IFS) provided by the International Monetary Fund. We supplement it with the GDP records provided by OECD Statistics, so that all countries in our sample have at least yearly GDP observations during the sample period. Next, we collect country-monthly industrial production indices and employment information. We get these information from Refinitiv Datastream. Then, we use the production indices and employment data to interpolate GDP on the country-month level.[7] Finally, we collect country-month level CPI data also from the IFS.

To measure a country's welfare, we get country-month level consumption data by interpolating the country-year level consumption series. First, we get country-year level consumption data from the IFS. Then, we acquire country-month level retail sales indices from Refinitiv Datastream, and interpolate the consumption data to country-month level with these series. For the countries of which the retail data is not available, we interpolate the consumption data with country-monthly GDP data.

International Trade and Gross Output We acquire country-bilateral and monthly international trade information from Direction of Trade Statistics (DOTS).[8] We get country-year level GDP to gross output ratio from the international input-output database constructed by Johnson and Noguera (2017), the long-run World Input-Output Database (Woltjer et al., 2021), and the OECD Analytical Activity of Multinational Enterprises Database (Cadestin et al., 2018). We get country-month level gross output by dividing country-month level GDP with the corresponding GDP to gross output ratio.

[7] In Appendix Section A.1, we describe the interpolation method.

[8] Similar to Caliendo and Parro (2015), we use the trade data that is reported on a cost, insurance and freight (CIF) basis.

With these datasets we identify, for each country that is directly hit by a disaster, its main upstream country (the country that the home country sources the most from) and main downstream country (the country that the home country sells the most to). We start with constructing country i's expenditure share on country j in month t, $\pi_{i,j,t}$. It equals the ratio of trade flow values from j to i, $x_{i,j,t}$, divided by the total expenditure on final (consumption and investment) and intermediate goods by country i, $X_{i,t}$:[9]

$$\pi_{i,j,t} = \frac{x_{i,j,t}}{X_{i,t}}.$$

Similarly, we define country i's output share to country k, $S_{k,i,t}$, as the ratio of trade flow values from i to k, $x_{k,i,t}$, divided by the gross output of country i, $Y_{i,t}$:

$$S_{k,i,t} = \frac{x_{k,i,t}}{Y_{i,t}}.$$

Such measures of expenditure and output shares ensure that for a specific country i in month t, the sum of expenditure shares on all upstream countries (including itself) and the sum of output shares to all downstream countries (including itself) both equal to 1: $\sum_{j=1}^{N} \pi_{i,j,t} = 1$ and $\sum_{k=1}^{N} S_{k,i,t} = 1$.

We define the **main upstream** country, j, as the one on which country i spends the largest share of expenditure:[10]

$$j(i,t) = \arg\max_{j \neq i} \pi_{i,j,t}.$$

We define the **main downstream** country, k, as the foreign country to which country i sells the largest share of output:

$$k(i,t) = \arg\max_{k \neq i} S_{k,i,t}.$$

[9] We construct country i's total expenditure in month t in the following way. Denote country i, month t's GDP with $GDP_{i,t}$ and country i, year y's GDP to gross output ratio with $VAS_{i,y}$. Then we measure country i, month t's total output with $Y_{i,t} = \frac{GDP_{i,t}}{VAS_{i,y(t)}}$ (we assume that a country's GDP share in the country's gross output ratio does not change within a year). We measure total expenditure on intermediate goods with $Y_{i,t} - GDP_{i,t}$. Total expenditure on final goods equals the country's GDP plus total imports minus total exports: $GDP_{i,t}+IM_{i,t}-EX_{i,t}$. Therefore, the country's total expenditure equals: $X_{i,t} = Y_{i,t}+IM_{i,t}-EX_{i,t}$.

[10] De Souza and Li (2020) employs a similar approach to identify the main upstream and downstream sectors of a sector protected by tariffs and study the upstream and downstream effects of these tariffs. They define the main upstream sector as the one from which the tariffed sector buys the largest share of input. They define the main downstream sector as the foreign country to which the tariffed sector sells the largest share of output.

Stock Market Measures We acquire country-sector level, country-aggregate level, and world-sector level daily stock market indices and returns from Refinitiv Datastream. From the same data source, we also get country-sector-month level stock market price-to-earnings ratio and earnings per share. We also acquire three-month government bond yield data for the sample economies.

Climate Disaster Data and Disaster Locations We acquire information about global climate disasters from the Emergency Events Database (EM-DAT).[11] We learn, for each disaster, the start and end date, monetary value of damage, affected persons, and total deaths.[12]

We then merge EM-DAT with the Geocoded Disasters (GDIS) Dataset (Rosvold and Buhaug, 2020). GDIS covers the latitude-longitude information of the geographical areas affected by each disaster in EM-DAT.

Transport Infrastructure Locations We obtain the latitude-longitude information of global transport infrastructure – in particular, ports – from the United Nations Code for Trade and Transport Locations Database. Using Geographical Information System (GIS) software, we project these infrastructures and the geographical areas affected by each climate disaster to the same map. In this way we identify whether each climate disaster hits a port.

Climate Risks To measure climate change risks, we rely on the Climate Change Exposure Index from Verisk Maplecroft. The index characterizes the degree to which countries may be exposed to the physical impacts of future climate disasters.[13] Since climate change

[11] The Emergency Events Database (EM-DAT) includes global disasters of all kinds. We only keep those that are related to climate: floods, storms (hurricanes), droughts, wildfires, and extreme temperatures. We 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 criteria that is used in International Monetary Fund (2020), we further restrict the sample to those that affected more than 0.5 percent of the country's population or caused a damage of 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.

[12] 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.

[13] The raw data use 0 to denote the highest risk and 10 to denote the lowest risk. To make the measure more intuitive, 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

risks generally refer to a long-term view, we fix a country's climate risk to its value in 2019.[14]

3 Empirical Strategy for the Macroeconomic Effects of Climate Disasters

To study the macroeconomic effects of climate disasters on affected countries and the foreign economies that trade intensively with the affected countries, we use a difference-in-differences event study strategy. We take the following steps. First, we identify the climate disasters that are eligible for the event study. Second, we match each country in the treatment group to a most similar counterpart and the latter forms the control group. Next, we link each country to their main trade partners to investigate how disasters spillover along the supply chain.

3.1 Eligible Climate Disasters

We examine the impact of a climate disaster from 4 months before the disaster start date to 4 months after the disaster start date. That is, for a specific disaster d that takes place in month t, we study the macroeconomic dynamics within the window $[t-4, t+4]$, where $[t-4, t-1]$ is the pre-period and $[t, t+4]$ is the post-treatment window.

We ensure that no other climate disasters happen in the pre-period of each disaster. That is, we keep the events whose windows do not overlap. If there is more than one disaster that hits the same country within 4 months, we drop all these disasters. In this way, we acquire a unique set of 430 climate disasters with non-overlapping event windows.

3.2 Difference-in-Differences

3.2.1 Midstream Home Country

We employ a matching-and-stacking difference-in-differences strategy. For each disaster d that hits country i in period t, we find a "clean" country, $i'(i, d, t)$, as the control group. $i'(i, d, t)$ is the country that is not hit by any climate disaster within the event window

change hazard index is therefore associated with higher climate risks.

[14]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.

and is the most similar to country i according to propensity score matching.[15] The treatment and control groups for each disaster d are then stacked into a new data set.[16] The regression specification is the following:

$$y_{i,d,t} = \sum_{m=-\bar{t}}^{\bar{t}} \beta_m \mathbb{I}_t \{m \text{ Months After Climate Disaster } d\} \frac{Damage_{i,d}}{GDP_{i,\bar{y}}} + \alpha_{i,d} + \lambda_{t,d} + \epsilon_{i,d,t}, \quad (1)$$

where $y_{i,d,t}$ denotes the outcome variable of country i in month t due to climate disaster d. $\mathbb{I}_t \{m \text{ Months After Climate Disaster } d\}$ is an indicator variable that takes value 1, if month t is m months away from the start of disaster d. To measure how the home economy is exposed to the disaster, we define the variable – **damage ratio**, $\frac{Damage_{i,d}}{GDP_{i,\bar{y}}}$, which equals the monetary loss from the disaster, $Damage_{i,d}$, divided by the home country's annual GDP in the year prior to the disaster, $GDP_{i,\bar{y}}$. β_m captures the impact of the disaster in month m. We set $\bar{t} = 4$.[17] As a standard practice in the stacked difference-in-differences literature, we use $\alpha_{i,d}$ to control the country-disaster fixed effect and $\lambda_{t,d}$ to control the disaster-time fixed effect. By controlling $\lambda_{t,d}$, we effectively estimate the treatment effect for each disaster first and then we take the average of all disasters. We cluster standard errors at country-disaster level.[18]

To investigate the average effect of a disaster over time (in an average month of the first four months after a disaster starts), we consider the following cross-sectional specification:

$$y_{i,d,t} = \beta \times Post_{d,t} \times \frac{Damage_{i,d}}{GDP_{i,\bar{y}}} + \alpha_{i,d} + \lambda_{t,d} + \epsilon_{idt}, \quad (2)$$

where $Post_{d,t}$ is an indicator variable which equals 1 if month t is after the start date of disaster d.

[15]The matching procedure is discussed in Appendix A.2. We also show that the result is robust across different matching mechanisms.

[16]Baker et al. (2022) argues that the stacked difference-in-differences design can address the potential bias due to staggered treatment timing and heterogeneous treatment effect in the standard two-way fixed effect difference-in-differences models. The stacked design pairs each treated country to a country that is otherwise similar but is never treated at least four months before the climate disaster, thus alleviating such bias. This method is also used in Cengiz et al. (2019) and Wache (2021), among others.

[17]To avoid collinearity, we code β_{-1} to 0. β_m should thus be interpreted as the relevant effect in regarding to period -1.

[18]We take a similar standard error clustering strategy as Baker et al. (2022), Cengiz et al. (2019), Choi and Shim (2021) and Wache (2021). The standard error is two-way clustered at country and pair level to avoid potential correlation across residuals caused by appearance of same countries.

3.2.2 Main Upstream and Downstream Countries

For each disaster d that hits country i, we define the main upstream and downstream countries as follows. First, we select the countries that are not affected by any climate disaster during the event window. Then, among these countries, we find the main upstream country as the foreign country on which country i spends the largest share of expenditure in the year before disaster d, using the definitions in Section 2 (call it country j). Similarly, we define the downstream country as the foreign country to which country i sells the largest share of output in the year before disaster d (call it country k). Throughout an event window, we fix the main upstream and downstream countries.

Next, we find the controls for the main upstream and downstream countries. Again we start with the countries that are not affected by climate disasters during the event window. Then, we exclude the main upstream j and main downstream k. Among the rest of the countries, we find, for the home country's control i', its main upstream j' and main downstream k'. We use j' as the control for j and k' as the control for k.

We use the following specification to study the impact of climate disasters on downstream countries:

$$y_{k,d,t} = \sum_{m=-\bar{t}}^{\bar{t}} \beta_m^{down} \mathbb{I}_t \left\{ m \text{ Months After Climate Disaster } d \right\} \frac{Damage_{i,d} \times S_{k,i,t}}{GDP_{k,\bar{y}}} + \alpha_{k,d} + \lambda_{t,d} + \epsilon_{k,d,t}. \tag{3}$$

$\frac{Damage_{i,d} \times S_{k,i,t}}{GDP_{k,\bar{y}}}$ measures downstream country k's exposure to the disaster (we refer to this variable as the **downstream exposure measure**). It takes into account two channels through which a disaster can affect the downstream economy: (1) shock propagation (captured by $Damage_{i,d}$), and (2) trade disruption (captured by dynamic output share $S_{k,i,t}$). Since $Damage_{i,d}$ measures the loss in output in the midstream, $Damage_{i,d} \times S_{k,i,t}$ captures the loss in trade flow values from midstream to downstream. Dividing it with the downstream country's annual GDP in the year before the disaster then measures how much the downstream is exposed to the disaster relative to its size.

Similar to before, $y_{k,d,t}$ denotes a macroeconomic variable of interest in downstream country k in month t due to disaster d. We control for the downstream-country-disaster and disaster-month fixed effects. We cluster standard errors at downstream-country-disaster level.

To study the time-average impact of a disaster on the downstream country, we use the following cross-sectional specification:

$$y_{k,d,t} = \beta \times Post_{d,t} \times \frac{Damage_{i,d} \times S_{k,i,t}}{GDP_{k,\bar{y}}} + \alpha_{k,d} + \lambda_{t,d} + \epsilon_{k,d,t}. \tag{4}$$

We use the following specification to study the impact of climate disasters on upstream countries:

$$y_{j,d,t} = \sum_{m=-\bar{t}}^{\bar{t}} \beta_m^{up} \mathbb{I}_t \{m \text{ Months After Climate Disaster } d\} \frac{Damage_{i,d} \times \pi_{i,j,t}}{GDP_{j,\bar{y}}} + \alpha_{j,d} + \lambda_{t,d} + \epsilon_{j,d,t}. \tag{5}$$

$\frac{Damage_{i,d} \times \pi_{i,j,t}}{GDP_{j,\bar{y}}}$ measures upstream country j's exposure to the disaster (we refer to this variable as the **upstream exposure measure**). Similar to the downstream effect, it takes into account two channels through which a disaster can affect the upstream economy: (1) shock propagation (captured by $Damage_{i,d}$), and (2) trade disruption (captured by dynamic expenditure share $\pi_{i,j,t}$). Since $Damage_{i,d}$ also measures the loss in income in the midstream, $Damage_{i,d} \times \pi_{i,j,t}$ captures the loss in trade flow values from upstream to midstream. Dividing it with the upstream country's annual GDP in the year before the disaster then measures how much the upstream is exposed to the disaster relative to its size.

Similar to the downstream specification, here $y_{j,d,t}$ denotes a macroeconomic variable of interest in upstream country j in month t due to disaster d. We control for the upstream-country-disaster and disaster-month fixed effects. We cluster standard errors at upstream-country-disaster level.

To study the time-average impact of a disaster on the upstream country, we use the following cross-sectional specification:

$$y_{j,d,t} = \beta \times Post_{d,t} \times \frac{Damage_{i,d} \times \pi_{i,j,t}}{GDP_{j,\bar{y}}} + \alpha_{j,d} + \lambda_{t,d} + \epsilon_{j,d,t}. \tag{6}$$

4 Macroeconomic Effects of Climate Disasters at Home and Abroad

4.1 Midstream Macroeconomic Effects

Figure 1 shows that a climate disaster significantly decreases the affected country's total exports, weakly decreases its GDP, and weakly increases the country's imports.[19] These results suggest that a climate disaster can disrupt domestic production. Thus, the home country has to rely more on foreign products and have fewer products to export to downstream countries.

These estimated dynamic effects imply that, in month 0, a climate disaster reduces the affected country's GDP by 0.50%, its exports by 1.05%, but increases its imports by 0.68% in month 4 (see Table 3). The impact of an average climate disaster is calculated by multiplying the coefficients in Figure 1, with the damage ratio of an average disaster summarized in Table A.1.

In Table 1, we show that, in an average month (of the first 4 months) after a climate disaster hits, the climate disaster significantly reduces the country's exports, weakly decreases its GDP, but weakly increases its imports. Table 3 shows that an average climate disaster reduces the country's exports by 0.62% in an average month. Table 1 also shows that climate disasters weakly reduce exports to the main downstream country and imports from the main upstream country.

Figure A.3 shows that a climate disaster increases the affected country's consumer price index from month 0 to month 2 after the disaster starts.

4.2 Only the Climate Disasters that Hit Ports Reduce Trade

To highlight that international trade is an important propagation mechanism, we show that the climate disasters that hit a transport infrastructure that is crucial for international trade – ports – lead to more disruptions in both international trade and domestic production. The climate disasters that do not hit ports do not have such effects. The critical role of ports in international trade is proven by the fact that 80% of global trade is conducted through ports (Sirimanne et al., 2019).

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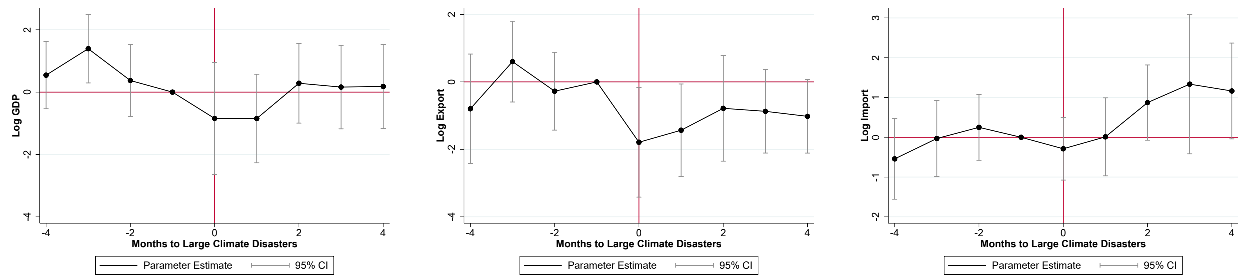
Figure 1: **Impact of Climate Disasters on Midstream Production and Trade**

(a) Aggregate GDP (b) Aggregate Export (c) Aggregate Import



Description: This figure contains the coefficients of the effect of a climate disaster on the log GDP, export and import of the country it directly hit using the stacked event-study model 1. The x-axis contains the number of months to the disaster's starting date. GDP data is obtained and estimated based on IMF and OECD statistics. Trade data is from the IMF DOT statistics. The sample is composed of countries hit by a large climate disaster and their control pairs. We constrain the sample to the set of countries observed 4 months around the disaster shock. The vertical gray segments contain the 95% confidence interval. Standard errors are two-way clustered at the country-disaster level.

Table 1: **Impact of Climate Disasters on Midstream Production and Trade**

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Log GDP	Log Export	Log Import	Log Export to Main Downstream	Log Import from Main Upstream
Damage Ratio	-0.790	-1.062*	0.700	-0.761	0.337
	(0.609)	(0.545)	(0.546)	(0.828)	(0.847)
Observations	7,740	7,740	7,740	7,740	7,740
Cou. X Dis. FE	Yes	Yes	Yes	Yes	Yes
Time X Dis. FE	Yes	Yes	Yes	Yes	Yes
Cluster	Dis.	Dis.	Dis.	Dis.	Dis.
Mean Dep. Var	8.416	20.68	20.89	19.09	19.26
R^2	0.190	0.193	0.149	0.513	0.280

Description: This table presents the estimated parameters of model 2. The sample is composed of countries hit by a large climate disaster and their control pairs. We constrain the sample to the set of countries observed 4 months around the disaster shock. "Damage Ratio" is the monetary loss caused by the disaster divided by home country's yearly GDP. Log GDP is the log of gross domestic production. Log Export is the log of aggregate export. Log Import is the log of aggregate import. Log Export to Main Downstream is the log of export from midstream country to its main downstream country (See Section 3.2.2). Log Import from Main Upstream is the log of midstream's import from its main upstream country (See Section 3.2.2). Standard errors are two-way clustered at the country-disaster level. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Figure 2 shows that the climate disasters that hit ports significantly reduce the affected country's exports and imports. Table 3 shows that, by multiplying the coefficients in the figures with the damage ratio of an average disaster summarized in Table A.1, in month 0, a climate disaster that hit ports significantly reduce exports by 0.54% and reduce imports by 0.26%.

Figure 2 also shows that the climate disasters that do not hit ports do not significantly reduce exports (due to a wide confidence interval). These disasters significantly increase imports in month 4. This evidence suggests the affected country replies more on foreign supplies. When the transport infrastructure is not affected, they import more. When ports are disrupted or even destroyed, the transportation cost of importing increases significantly. In this case, the loss in income effect dominates, which causes a decline in imports.[20]

Figure 3 shows that climate disasters that hit ports also significantly reduce exports to the main downstream country and imports from the main upstream country. However, climate disasters that do not hit ports do not have such significant effects on the affected country's bilateral trade with main upstream and downstream countries. This shows that, climate disasters, if they hit the port infrastructure, can propagate to downstream and upstream countries through trade.

In Table 2, we show that in an average month of the first 4 months after a climate disaster hits, if the disaster hits a port, the disaster will significantly reduce GDP, exports, imports, exports to the main downstream country, and imports from the main upstream country. However, if the disaster does not hit a port, the disaster does not significantly affect GDP, exports, exports to the main downstream, and imports from the main upstream. But the disaster that does not hit a port significantly increases imports from the main upstream. In Table 3, we show that an average disaster that hits a port decreases the country's GDP by 0.45%, exports by 0.47%, imports by 0.11%, exports to the main downstream country by 0.87%, and imports from the main upstream country by 0.44%. In contrast, an average disaster that does not hit a port only significantly increases imports by 1.10%, but it does not significantly affect other aggregate variables on production or trade.

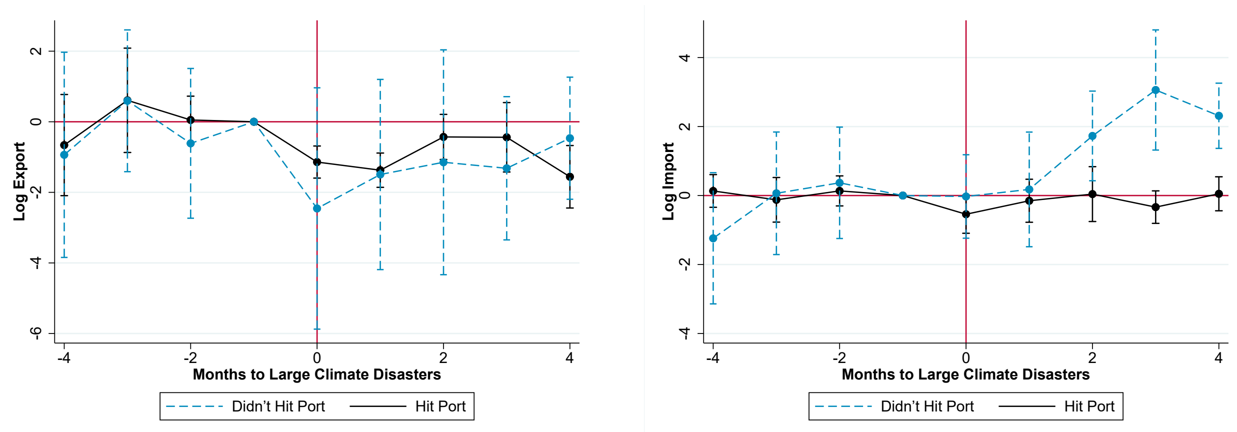
4.3 Cross-border Spillover Effects on Main Trade Partners

In this section, we show that the climate disasters that affect international trade infrastructures can significant undermine economic performance in upstream and downstream countries. This indicates that a country can be negatively impacted by not only their own climate disasters, but also those that hit their main trade partners. Again, by comparing

[20] In Appendix Figure A.4 we show that climate disasters that hit ports reduce the affected country's GDP more than those that do not hit ports.

Figure 2: **Impact of Climate Disasters on Midstream Trade by Whether They Hit a Port**

(a) Aggregate Export (b) Aggregate Import



Description: This figure contains the coefficients of the effect of a climate disaster on the log export and import of the country it directly hit using the stacked event-study model 1. The x-axis contains the number of months to the disaster's starting date. Trade data is from the IMF DOT statistics. The sample is composed of countries hit by a large climate disaster and their control pairs. We constrain the sample to the set of countries observed 4 months around the disaster shock. The sample is split into 2 sub-samples. One contains disasters that affect at least one local port, the other contains disasters that don't hit any port. The black curve and vertical segments contain coefficients and 95% CI based on the "Hit Port" sub-sample. The blue dashed curve and vertical segments contain coefficients and 95% CI based on the "Didn't Hit Port" sub-sample. Standard errors are two-way clustered at the country-disaster level.

the disasters that hit ports versus those that do not hit ports, we confirm that international trade is an important propagation mechanism.

Figure 4a shows that climate disasters that hit ports significant reduce GDP in main downstream countries. However, downstream GDP is not significantly affected by the disasters that do not hit ports. Similarly, Figure 4b shows that climate disasters that hit ports also significantly reduce upstream GDP, but those that do not hit ports have no such significant effect. Multiplying the coefficients displayed in the event study figures with the mean of the exposure measures in Table A.1, we learn that a climate disaster decreases the downstream country's GDP by 0.51% and the upstream country's GDP by 0.36% in the first month after a disaster hits a port (see Table 5).

Table 4 shows that in an average month after a disaster hits, the disaster significantly reduces both downstream and upstream GDP if it hits a port, but doesn't if it does not hit a port. On average, a climate disaster significantly reduces downstream GDP but does not significantly affect upstream GDP. The second effect is consistent with what we find in Section 4.1: an average climate disaster does not reduce imports, nor the imports from the main upstream country. Table 5 shows that in an average month, a climate disaster that hits ports reduce downstream GDP by 0.38% and upstream GDP by 0.35%.

Climate Disasters on Foreign Aggregate Trade and Price Figure A.5 shows that a climate disaster only weakly decreases both total imports by the downstream country and

Table 2: **Impact of Climate Disasters on Midstream Production and Trade by Whether They Hit a Port**

VARIABLES	(1) Log GDP	(2) Log Export	(3) Log Import	(4) Log Export to Main Downstream	(5) Log Import from Main Upstream
Panel A: Disasters that didn't hit port					
Damage Ratio	-0.621	-1.138	1.652**	0.347	1.642
	(1.184)	(1.110)	(0.688)	(1.166)	(1.252)
Observations	4,554	4,554	4,554	4,554	4,554
Cou. X Dis. FE	Yes	Yes	Yes	Yes	Yes
Time X Dis. FE	Yes	Yes	Yes	Yes	Yes
Cluster	Dis.	Dis.	Dis.	Dis.	Dis.
Mean Dep. Var	8.416	20.68	20.89	19.09	19.26
R^2	0.215	0.222	0.164	0.587	0.330
Panel B: Disasters that hit port					
Damage Ratio	-0.954***	-0.988***	-0.223**	-1.835***	-0.928***
	(0.205)	(0.277)	(0.110)	(0.496)	(0.296)
Observations	3,186	3,186	3,186	3,186	3,186
Cou. X Dis. FE	Yes	Yes	Yes	Yes	Yes
Time X Dis. FE	Yes	Yes	Yes	Yes	Yes
Cluster	Dis.	Dis.	Dis.	Dis.	Dis.
Mean Dep. Var	8.416	20.68	20.89	19.09	19.26
R^2	0.148	0.141	0.124	0.381	0.186

Description: This table presents the estimated parameters of model 2. The sample is composed of countries hit by a large climate disaster and their control pairs. We constrain the sample to the set of countries observed 4 months around the disaster shock. The sample is split into 2 sub-samples. One contains disasters that affect at least one local port, the other contains disasters that don't hit any port. "Damage Ratio" is the monetary loss caused by the disaster divided by home country's yearly GDP. Log GDP is the log of gross domestic production. Log Export is the log of aggregate export. Log Import is the log of aggregate import. Log Export to Main Downstream is the log of export from midstream country to its main downstream country (See Section 3.2.2). Log Import from Main Upstream is the log of midstream's import from its main upstream country (See Section 3.2.2). Standard errors are two-way clustered at the country-disaster level. Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

total exports by the upstream country. Since we have shown in Figure 3 that climate disasters significantly reduce the downstream country's imports and the upstream country's exports with the affected country, this suggests that foreign countries substitute their suppliers and customers from the disaster-hit country to offset the decline in bilateral trade. Likely due to such substitution, as shown in Appendix Figure A.6, we find no evidence that a climate disaster causes inflation or deflation in downstream and upstream countries.

Climate Disasters on Foreign Emerging Market and Developing Economies Appendix Table A.4 shows that emerging market and developing economies are more vulnerable to

Table 3: **Interpret the Damage Effect in Home Country**

VARIABLES	(1) Log GDP	(2) Log Export	(3) Log Import	(4) Log Export to Main Downstream	(5) Log Import from Main Upstream
All Disasters					
Effect at month 0	-0.496%	-1.051%**	-0.169%	-0.442%	-1.698%
Average Effect in 4 month	-0.464%	-0.624%*	0.411%	-0.447%	-0.198%
Disasters that hit port					
Effect at month 0	-0.358%**	-0.539%***	-0.256%*	-0.958%***	-0.890%***
Average Effect in 4 month	-0.451%***	-0.467%***	-0.105%**	-0.867%***	-0.439%***
Disasters that didn't hit port					
Effect at month 0	-0.624%	-1.640%	-0.018%	0.375%	-2.624%
Average Effect in 4 month	-0.415%	-0.760%	1.103%**	0.232%	1.096%

Description: This table presents the damage effect on macroeconomic indicators in disaster-hit home country. The effect size is calculated based on the coefficients from model 1 and 2. We interpret the coefficients by multiplying them by a sample mean of damage ratio. *** p<0.01, ** p<0.05, * p<0.1.

foreign climate disasters. We add to the cross-section specifications 4 and 6 a dummy that indicates whether the midstream, upstream, or downstream country is an emerging market or developing economy, and its interaction with the exposure measure. The table shows that a climate disaster has more adverse consequence on the downstream or upstream country if it is an emerging market or developing economy. The likely reason is that emerging market and developing economies are less able to switch suppliers or customers, so they bear greater consequence of foreign climate disasters. However, conditional on how upstream and downstream countries are exposed to a climate disaster, whether disaster-hit country is an emerging market or developing economy does not significantly affect the cross-border spillover effect.

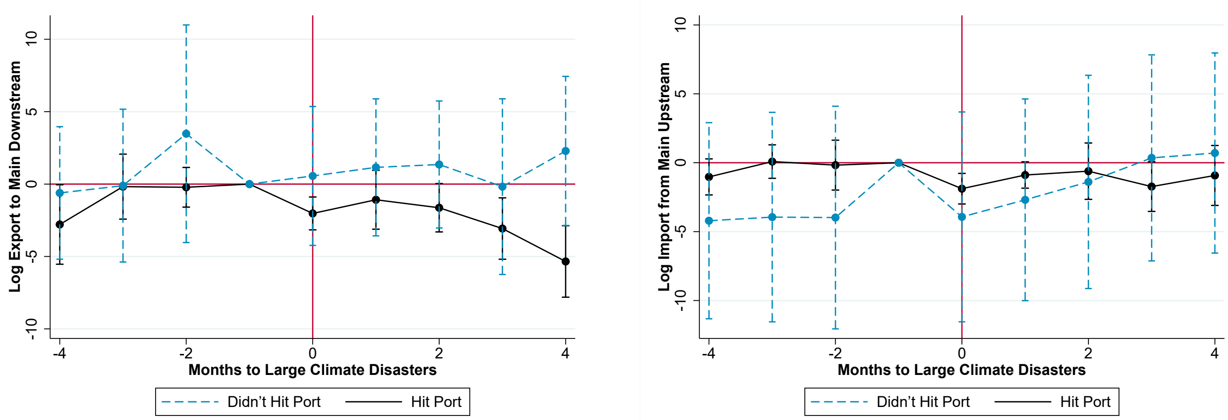
Table 4: **Disaster Effect on Foreign Country Production**

VARIABLES	(1) Log Downstream GDP	(2) Log Upstream GDP	(3) Log Downstream GDP	(4) Log Upstream GDP	(5) Log Downstream GDP	(6) Log Upstream GDP
	Full Sample		Hit Port Sample		Didn't Hit Port Sample	
Exposure to Foreign Disaster	-312.4*	-223.1	-796.3**	-482.2**	-172.1	-15.77
	(162.7)	(167.8)	(390.7)	(231.0)	(202.7)	(177.6)
Observations	7,740	7,740	3,186	3,186	4,554	4,554
Cou. X Dis. FE	Yes	Yes	Yes	Yes	Yes	Yes
Time X Dis. FE	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Dis.	Dis.	Dis.	Dis.	Dis.	Dis.
Mean Dep. Var	12.16	11.96	12.16	11.96	12.16	11.96
R^2	0.0842	0.0802	0.0759	0.0730	0.0895	0.0848

Description: This table presents the estimated parameters of model 6 and 4. The sample is composed of midstream country's main trade partners and their control pairs. We constrain the sample to the set of countries observed 4 months around the disaster shock. The sample is split into 2 sub-samples. One contains disasters that affect at least one local port, the other contains disasters that don't hit any port. "Exposure to Foreign Disaster" is the monetary loss in the midstream country divided by downstream or upstream country's yearly GDP $\times$ output share or expenditure share of the home country on the trade partners. Log GDP is the log of gross domestic production. Columns 1-2 report results from the full sample. Columns 3-4 report results for disasters that hit at least one port. Columns 5-6 report results for disasters that did not affect any port. Standard errors are two-way clustered at the country-disaster level. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Figure 3: **Impact of Climate Disasters on Midstream Bilateral Trade by Whether They Hit a Port**

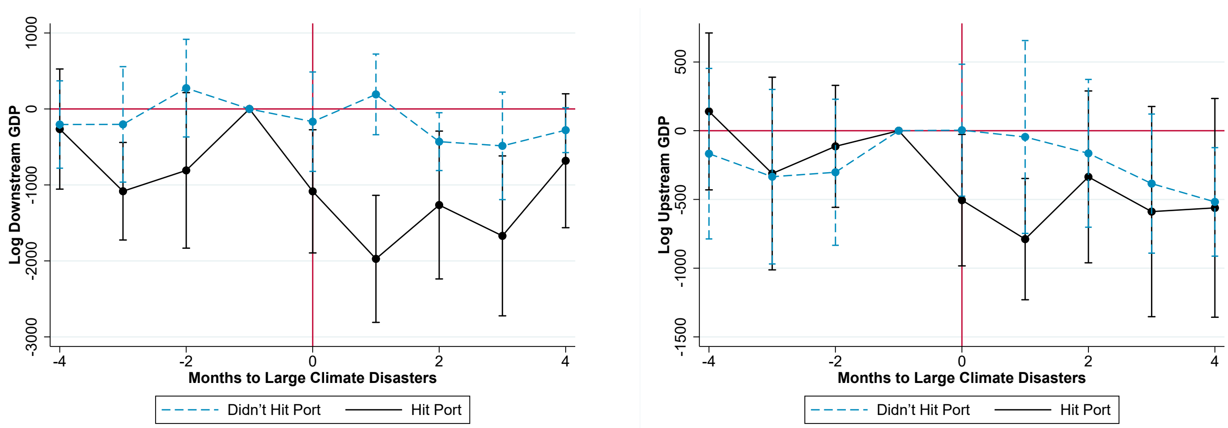
(a) Export to Main Downstream (b) Import from Main Upstream



Description: This figure contains the coefficients of the effect of a climate disaster on the log export and import of the country it directly hit using the stacked event-study model 1. The x-axis contains the number of months to the disaster's starting date. Trade data is from the IMF DOT statistics. We use the bilateral trade between a midstream country to its main upstream and main downstream country (as defined in Sector 3.2.2) as independent variable. The sample is composed of countries hit by a large climate disaster and their control pairs. We constrain the sample to the set of countries observed 4 months around the disaster shock. The sample is split into 2 sub-samples. One contains disasters that affect at least one local port, the other contains disasters that don't hit any port. The black curve and vertical segments contain coefficients and 95% CI based on the "Hit Port" sub-sample. The blue dashed curve and vertical segments contain coefficients and 95% CI based on the "Didn't Hit Port" sub-sample. Standard errors are two-way clustered at the country-disaster level.

Figure 4: **Impact of Climate Disasters on Downstream and Upstream Production by Whether They Hit a Port**

(a) Downstream GDP (b) Upstream GDP



Description: This figure contains the coefficients of the effect of a climate disaster on the log GDP of the midstream country's main downward and upward trade partners using the stacked event-study model 3 and 5. The x-axis contains the number of months to the disaster's starting date. GDP data is obtained and estimated based on IMF and OECD statistics. The sample is composed of midstream country's main trade partners and their control pairs. We constrain the sample to the set of countries observed 4 months around the disaster shock. The sample is split into 2 sub-samples. One contains disasters that affect at least one local port, the other contains disasters that don't hit any port. The black curve and vertical segments contain coefficients and 95% CI based on the "Hit Port" sub-sample. The blue dashed curve and vertical segments contain coefficients and 95% CI based on the "Didn't Hit Port" sub-sample. Standard errors are two-way clustered at the country-disaster level.

4.4 Trade Disruption

We refer to trade disruption as how exports and imports are disrupted relative to total output and total expenditure.[21] If, for example, exports decrease more relative to total

[21] When a part of the international trade network is hit by a shock, countries restructure their supply chain by sourcing more from and selling more to the part of the world that is less affected by the shock. This leads

Table 5: **Interpret the Spillover Effect on Foreign Production**

VARIABLES	(1) Log Downstream GDP	(2) Log Upstream GDP	(3) Log Downstream GDP	(4) Log Upstream GDP	(5) Log Downstream GDP	(6) Log Upstream GDP
	Full Sample		Hit Port Sample		Didn't Hit Port Sample	
Effect at month 0	-0.209%	-0.163%	-0.512%**	-0.361%**	-0.101%	-0.003%
Average Effect in 4 month	-0.172%*	-0.160%	-0.376%**	-0.345%**	-0.104%	-0.011%

Description: This table presents the damage effect on GDP in disaster-hit home country's main trade partners. The effect size is calculated based on the coefficients from model 6 and 4. We interpret the coefficients by multiplying them by a sample mean of exposure measure. *** p<0.01, ** p<0.05, * p<0.1.

output – the export share decreases, we say that exports are disrupted. Otherwise, they are strengthened.

Figure 5a shows that a climate disaster only weakly decreases the affected country's export share, whether the disaster hits a port.[22] While exports decline and decline even more for the disasters that hit ports, the country's total output decline by a similar magnitude. This suggests that climate disasters, if anything, only weakly disrupts exports.

However, Figure 5b shows that, due to climate disasters, countries become more reliant on foreign supplies. The disasters that hit a port decrease imports but decrease total income even more, leading to an increase in the import share. The disasters that do not hit ports increase imports significantly, leading to even larger increase in the import share. This shows that climate disasters strengthen imports, and more so if the disasters do not hit ports. A weakly lower export share and a higher import share suggest that climate disasters increase countries' trade deficits and worsen their external balance.

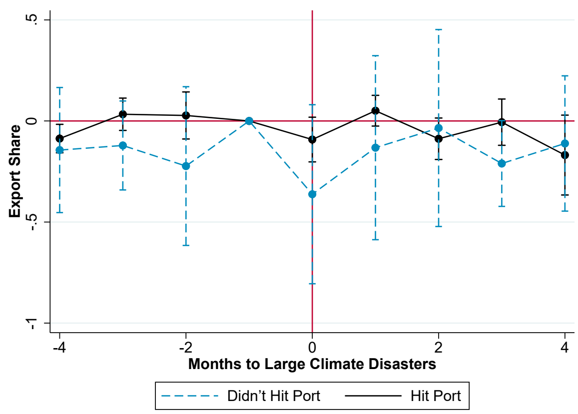
Figure 6a shows that climate disasters that hit ports significantly decrease the affected country's output share to the main downstream country ($S_{k,i,t}$ in Equation 3) and significantly increase the country's expenditure share on the main upstream country ($\pi_{i,j,t}$ in Equation 5). Table 6 shows the effect in an average month after the disaster and confirms these results. The estimated coefficients imply that, in an average month, a climate disaster that hits ports decreases the affected country's output share to the main downstream country by 2.1% but increases its expenditure share on the main upstream country by 2.6%.

Since export disruption may cause additional output loss in the downstream country and import strengthening may reduce the output loss in the upstream country (compared to a global trade network where the trade shares are not affected by climate disasters), in Section 4.5, we conduct a decomposition that helps understand the contributions by supply and demand shocks (without any disruption in trade) and trade disruption.

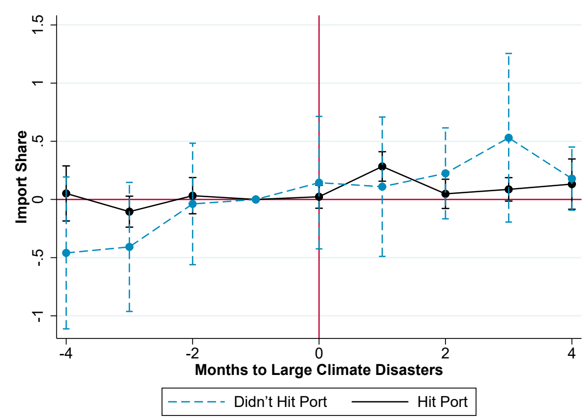
to changes in a country's market shares in other countries, i.e. trade disruptions. This is a prominent feature of international trade network that differentiates it from sectoral input-output production linkages, which

Figure 5: **Impact of Climate Disasters on Midstream Trade Share**

(a) Export Share



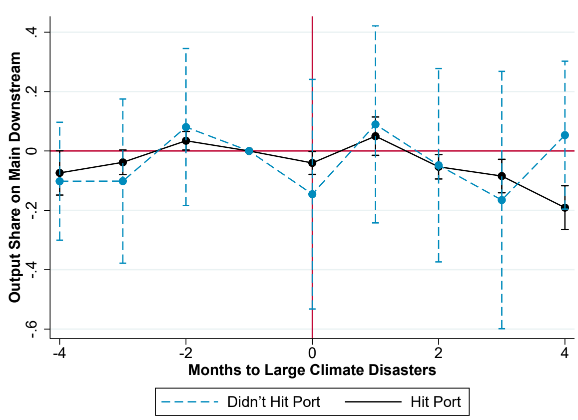
(b) Import Share



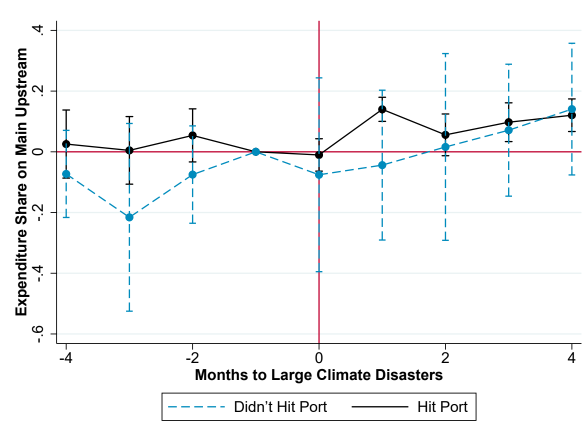
Description: This figure contains the coefficients of the effect of a climate disaster on the log export and import of the country it directly hit using the stacked event-study model 1. The x-axis contains the number of months to the disaster's starting date. Export share is midstream country's aggregate export divided by its aggregate output. Import share is midstream country's aggregate import divided by its aggregate expenditure. The sample is composed of countries hit by a large climate disaster and their control pairs. We constrain the sample to the set of countries observed 4 months around the disaster shock. The sample is split into 2 sub-samples. One contains disasters that affect at least one local port, the other contains disasters that don't hit any port. The black curve and vertical segments contain coefficients and 95% CI based on the "Hit Port" sub-sample. The blue dashed curve and vertical segments contain coefficients and 95% CI based on the "Didn't Hit Port" sub-sample. Standard errors are two-way clustered at the country-disaster level.

Figure 6: **Impact of Climate Disasters on Midstream Output and Expenditure Share**

(a) Output Share on Main Downstream



(b) Expenditure Share on Main Upstream



Description: This figure contains the coefficients of the effect of a climate disaster on the log export and import of the country it directly hit using the stacked event-study model 1. The x-axis contains the number of months to the disaster's starting date. Output share is the trade flow between midstream country and its main downstream partner divided by midstream's aggregate output. Expenditure share is the trade flow between midstream and its main upstream partner divided by midstream's aggregate expenditure. Output share and expenditure share are estimated using trade and GDP records. The sample is composed of countries hit by a large climate disaster and their control pairs. We constrain the sample to the set of countries observed 4 months around the disaster shock. The sample is split into 2 sub-samples. One contains disasters that affect at least one local port, the other contains disasters that don't hit any port. The black curve and vertical segments contain coefficients and 95% CI based on the "Hit Port" sub-sample. The blue dashed curve and vertical segments contain coefficients and 95% CI based on the "Didn't Hit Port" sub-sample. Standard errors are two-way clustered at the country-disaster level.

is generally considered fixed by the production technology.

[22]The export share refers to the midstream country's total exports divided by its total output. The import share refers to the midstream country's total imports divided by its total expenditure.

Table 6: **Disaster Effect on Midstream's Output and Expenditure share**

VARIABLES	(1) Output Share	(2) Expenditure Share	(3) Output Share	(4) Expenditure Share	(5) Output Share	(6) Expenditure Share
	Full Sample		Hit Port Sample		Didn't Hit Port Sample	
Damage ratio	-0.0287	0.0857	-0.0444***	0.0596**	-0.0125	0.113
	(0.0406)	(0.0522)	(0.0128)	(0.0254)	(0.0808)	(0.112)
Observations	7,740	7,740	3,186	3,186	4,554	4,554
Cou. X Dis. FE	Yes	Yes	Yes	Yes	Yes	Yes
Time X Dis. FE	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Dis.	Dis.	Dis.	Dis.	Dis.	Dis.
Mean Dep. Var	0.0368	0.0388	0.0368	0.0388	0.0368	0.0388
R^2	0.0186	0.0161	0.00943	0.0144	0.0229	0.0171

Description: This table presents the estimated parameters of model 2. The sample is composed of midstream country's main trade partners and their control pairs. We constrain the sample to the set of countries observed 4 months around the disaster shock. The sample is split into 2 sub-samples. One contains disasters that affect at least one local port, the other contains disasters that don't hit any port. "Damage Ratio" is the monetary loss caused by the disaster divided by home country's yearly GDP. Output share and expenditure share are estimated using trade and GDP records. We use the output and expenditure share between a midstream country to its main upstream and main downstream country (as defined in Sector 3.2.2) as independent variable. Columns 1-2 report results from the full sample. Columns 3-4 report results for disasters that hit at least one port. Columns 5-6 report results for disasters that did not affect any port. Standard errors are two-way clustered at the country-disaster level. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

4.5 Contribution by Trade Disruption to the Cross-border Spillover Effect

We investigate how the impact of a climate disaster on a foreign country depends on the trade disruption that it causes. A climate disaster reduces the affected country's total supply of intermediate input and final goods to downstream countries and reduce the country's total demand of these goods from upstream countries. Meanwhile, as we show in Section 4.4, a climate disaster can disrupt trade and restructure international supply chains. If the trade disruption makes upstream and downstream countries less open to trade, total output and welfare of upstream and downstream countries may be negatively impacted (see, for example, Arkolakis et al. 2012). Both channels – (1) supply and demand shocks (conditional on fixed shares of trade) and (2) trade openness (or its reverse, trade disruption) – contribute to the negative consequences of climate disasters in upstream and downstream economic performances.

We provide a new decomposition formula that sheds light on the contributions by the two channels. First, consider the impact of a climate disaster on downstream countries. As we show in Appendix Section B, the disaster affects downstream country k's output according to the following equation:

$$\text{dlog}(GDP_{k,t}) = \underbrace{\frac{\text{Damage}_{i,d} S_{k,i,\bar{y}}}{GDP_{k,\bar{y}}}}_{\text{Supply Shock}} + \underbrace{\pi_{k,i,t}\,\text{dlog}(S_{k,i,t})}_{\text{Trade Openness}}, \tag{7}$$

where, similar to Equation 3, the supply shock measures how the downstream country is exposed to the disaster. The difference is that here the midstream's share of output to the downstream is held as fixed.[23] If disasters did not disrupt trade at all, the midstream country i's exports would decrease by the disaster's damage split among all downstream countries, according to the midstream country's fixed output shares. Such loss is then divided with the downstream GDP in the previous year to get the downstream exposure measure.

The trade disruption term consists of the percentage change in the output share, which summarizes the extent that midstream exports decline relative to midstream total output, and the downstream expenditure share on the midstream, which measures how the downstream country is exposed to such trade disruption.

To investigate how both channels contribute to a climate disaster's impact on the downstream country, we consider the following specification:

$$y_{k,d,t} = \underbrace{\beta_1 \times Post_{d,t} \times \frac{\text{Damage}_{i,d} \times S_{k,i,\bar{y}}}{GDP_{k,\bar{y}}}}_{\text{Supply Shock}} + \underbrace{\beta_2 \times Post_{d,t} \times \frac{\pi_{k,i,t}}{S_{k,i,t}} \widehat{d(S_{k,i,d})}}_{\text{Trade Openness}} + \alpha_{k,d} + \lambda_{t,d} + \epsilon_{k,d,t}, \tag{8}$$

where, on the right hand side, we interact both the supply shock and trade disruption with a dummy that indicates whether month t is after the start date of disaster d. To measure the trade disruption that a disaster causes, we use its estimated effect on the midstream country's output share to the downstream predicted by Equation 4 in Section 4.4 (denoted with $\widehat{d(S_{k,i,d})}$). The definition of other variables in this regression is the same as those in Equations 4 and 7.[24] We limit our sample to the climate disasters that hit ports.

Similarly, we study how the demand shock and trade disruption affect upstream GDP with the following estimation strategy:

$$y_{j,d,t} = \underbrace{\beta_1 \times Post_{d,t} \times \frac{\text{Damage}_{i,d} \times \pi_{i,j,\bar{y}}}{GDP_{j,\bar{y}}}}_{\text{Demand Shock}} + \underbrace{\beta_2 \times Post_{d,t} \times \frac{S_{i,j,t}}{\pi_{i,j,t}} \widehat{d(\pi_{i,j,d})}}_{\text{Trade Openness}} + \alpha_{j,d} + \lambda_{t,d} + \epsilon_{j,d,t}, \tag{9}$$

where, on the right hand side, $\widehat{d(\pi_{i,j,d})}$ denotes the estimated effect of disaster d on country

[23] In the data, we set $S_{k,i,\bar{y}}$ to its average value in the year prior to the climate disaster.

[24] We show how we derive this formula in Appendix Section B. A similar decomposition is used in Mondragon and Wieland (2022).

i's expenditure share spent over j, which is predicted by Equation 6 in Section 4.4.[25]

Results Table B.1 shows that, even if we fix the expenditure and output shares, climate disasters still pose a negative supply shock to downstream countries and a negative demand shock to upstream countries. Therefore, they lead to GDP declines in those countries.

The trade disruption channel leads to negative GDP effect in downstream countries, but positive such effect in upstream countries.Table B.1 shows that openness to trade (measured with higher expenditure shares on upstream foreign countries and higher output shares to downstream foreign countries) increases GDP in both upstream and downstream countries.[26] The effect of a higher output share that the midstream sells to the downstream on downstream GDP is small, but the effect of a higher expenditure share that the midstream spends on the upstream on upstream GDP is much larger.[27] In Section 4.4, we find that climate disasters significantly reduce a country's output share to downstream countries, but significantly increase the country's expenditure share on upstream countries. Therefore, trade disruptions amplify the negative consequence of climate disasters on downstream countries. However, since the trade linkage with upstream foreign countries is strengthened, such supply chain restructuring alleviates the negative consequence of climate disasters on upstream countries.

Table B.1 shows that the supply shock channel contributes 97.6% and the trade disruption channel contributes 2.4% to the negative GDP effect in downstream countries.[28] On the other hand, the demand shock channel contributes 146.6% and the supply chain reorganization channel contributes -46.6%. The second result indicates that while a disaster reduces the affected country's total income and expenditure, it forces the country to spend a greater share on foreign suppliers, and the latter channel benefits these foreign countries. Such asymmetric trade disruption effects in upstream and downstream countries again confirm that international trade is an important propagation mechanism.

[25] We show how we derive this formula in Appendix Section B.

[26] This is consistent with previous works in the international trade literature which suggests that openness to trade leads to welfare and productivity gains. See Arkolakis et al. (2012).

[27] Both effects are significant. The estimated coefficients in Table B.1 implies that for an average disaster that hits ports, through the trade disruption channel, reduces the downstream country's GDP by 0.01%, but increases the upstream country's GDP by 0.11%.

[28] We define a channel's contribution, for example, that of a supply shock to downstream GDP, as follows: $\frac{\text{Cov}(\text{Supply Shock}_{i,d}, \text{Supply Shock}_{i,d} + \text{Trade Openness}_{i,d})}{\text{Var}(\text{Supply Shock}_{i,d} + \text{Trade Openness}_{i,d})}$. $\text{Supply Shock}_{i,d}$ and $\text{Trade Openness}_{i,d}$ are defined in Equation B.2. To construct these variables, we use the estimated coefficients. A similar decomposition formula is used in, for example, Li (2021).

4.6 Robustness and Other Findings

Impact of an Average Climate Disaster We may also estimate the impact of an average climate disaster by replacing the damage ratio in Equation 1 and the downstream and upstream exposure measures in Equations 3 and 5 with a dummy variable which equals 1 if the midstream country is hit by a climate disaster. Appendix Figure A.7 shows that an average climate disaster weakly decreases domestic GDP, import and export. Climate disasters that hit ports reduce midstream's trade with its main downstream and upstream partners and decrease GDP in these countries. Climate disasters that do not hit ports do not significantly affect such trade and downstream and upstream output.

Interacting Disaster Exposures with Port Dummy Appendix Table A.2 and Appendix Table A.3 include a regressor where we interact the exposures to foreign climate disasters with a dummy that equals one if the climate disaster hits ports. Similar to the split-sample analysis in the text, we find that climate disasters have more adverse impacts on international trade with main downstream and upstream countries and on these important trade partners' GDP if the disasters hit a port.

Different Measures of GDP We use GDP per capita, detrended GDP, and seasonal adjusted GDP as alternative measures for production.[29] Appendix Figure A.9 and A.10 suggest that our findings in the main analysis are robust across these different measures.

Other Transport Infrastructure: Airport In Appendix Figure A.11, we show that the climate disasters that hit airports reduce domestic GDP more than those that do not hit airports. However, we find no evidence that whether climate disasters hit airports affects the impact of climate disasters on foreign GDP. Since airports are much less important than ports in carrying international trade, this finding demonstrates that international trade propagates climate disasters across borders.

Whether the Main Downstream is also the Main Upstream We investigate the cross-border spillover effects of climate disasters by separately investigating (1) the downstream countries that are not the affected countries' main upstream countries, (2) the upstream countries that are not the affected countries' main downstream countries, and (3)

[29] To detrend the GDP sequence, we run a linear regression of time against log GDP and remove the estimated trend. We use HP-filter to remove the cycles from log GDP sequence to obtain the seasonal adjusted GDP.

the foreign countries that are both main upstream and main downstream. Appendix Figure A.12 shows that the foreign GDP decreases in all 3 groups if the climate disaster hits a port, and it decreases more in the foreign countries that are both main upstream and main downstream of the countries that are directly affected.

Geographical Propagation We study how climate disasters propagate according to geographical distance. We consider regressions similar to Equations 4 and 6, but we replace the exposure measures with a dummy that takes 1 if the midstream country is affected by a climate disaster, which we further interact with the distance measures commonly used in the trade gravity literature (Anderson and Van Wincoop, 2004). In Appendix Table A.5, we show only weak evidence that the countries that are farther away and not contiguous with the affected country are less affected by the cross-border spillover effects. This suggests that how close countries are in distance is not the only factor that governs the effects we find, and exposures to trade with the disaster-hit country are more important in explaining these effects.

Impact on Consumption and Welfare Following Lucas (1987), Jones and Klenow (2016), among others, we use the impact on consumption to measure how climate disasters affect household welfare. In Figure A.14, we show that, similar to the effects on production, climate disasters significantly reduce consumption and welfare in both the home country and the main international trade partners if they hit ports.

5 Impact of Climate Disasters on Stock Market Returns in Main Trade Partners

We take a financial market event study approach to investigate how climate disasters affect stock market returns in the main trade partners.[30] Since the stock market data is available not only on the country level but also on the country-sector level, research on the stock market helps us understand the cross-sector heterogeneity in how climate disasters affect the economic performance in main trade partner countries. The stock market data also allows us to investigate such impacts at higher frequencies.

In the financial market event study, different from the study on the real economy, we use the counterfactual (or "normal") returns predicted by the Capital Asset Pricing Model

[30]See MacKinlay (1997) for the standard procedure that researchers take to conduct a financial market event study.

(CAPM, Treynor 1961, Sharpe 1964, Lintner 1965), whose coefficients are estimated based on the relationship between the asset's returns and the aggregate market's returns in the pre-period (or the "estimation window"). The difference between the actual returns and the normal returns on each day in the event window forms the "abnormal returns", which capture the daily impact of the climate disaster on the stock market returns. Aggregating the daily abnormal returns throughout the event window gives the "cumulative abnormal returns", which measure the impact of the climate disaster on the stock market's total returns during the event window.

We use the following specification to study the downstream stock market effect of climate disasters. Use $RE^s_{k,t}$ to denote the return of downstream country k, sector s stock index on day t.[31] Subtracting the risk free rate (measured with the 3-month government bond yield in country k, $r^f_{k,t}$), we get the excess return: $re^s_{k,t} = RE^s_{k,t} - r^f_{k,t}$. The CAPM predicts the following relationship between the daily country-sector level stock excess returns and aggregate excess returns:

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

where $re^s_{global,t}$ denotes the excess returns on a global, sector s stock index (the index' return subtracting 3-month US government bond yield) and $re^{mkt}_{k,t}$ denotes the excess returns on downstream country k's aggregate market index.

For each disaster d that hits on date t, we estimate this model with the estimation window that starts 12 months before the disaster start date and ends one month before the disaster, i.e. $[t-12, t-1]$ in months or $[t-240, t-21]$ in trading days.[32] The estimated coefficients $\widehat{\beta^s_{0,k}}$, $\widehat{\beta^s_{1,k}}$, and $\widehat{\beta^s_{2,k}}$ relate the country-sector normal return to the world level return on this sector and the country-level aggregate market return.[33] Similar to the study on the real economy, we consider the event window $[t-1, t+4]$ in months or $[t-20, t+80]$ in trading days. Using the estimated coefficients, we compute the daily abnormal returns and the cumulative abnormal returns in the event window:

$$AR^s_{k,\tau} = re^s_{k,\tau} - \widehat{\beta^s_{0,k}} - \widehat{\beta^s_{1,k}} re^s_{global,\tau} - \widehat{\beta^s_{2,k}}\, re^{mkt}_{k,\tau}\text{ , where } \tau \in [t-20, t+80]$$

$$CAR^s_{k,x} = \sum_{\tau=t-20}^{t-20+x} AR^s_{k,\tau}\text{ , where } x \in [0, 100].$$

[31] We examine the same set of main downstream countries as the study on the macroeconomic effects. The aggregate stock market is denoted with $s = mkt$.

[32] To simply our calculation, we assume that there are 20 trading days in each month. In reality, there may be 20 or 21 trading days in a month, depending on the month.

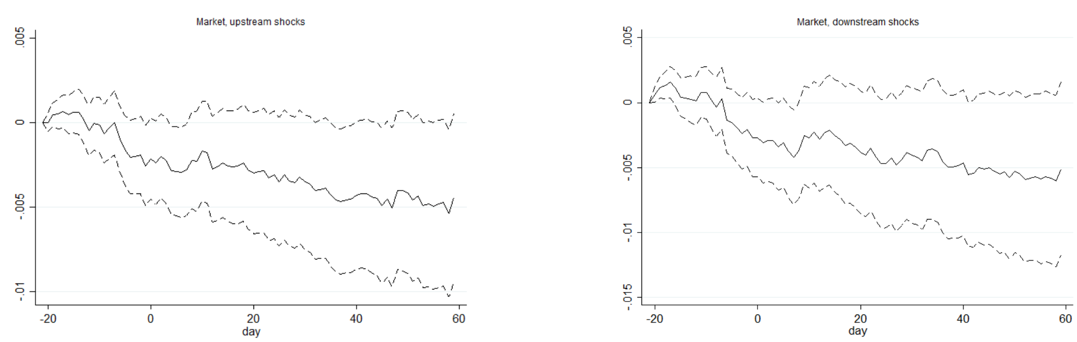
[33] The estimated coefficients are $\widehat{\beta^{mkt}_{0,k}}$, $\widehat{\beta^{mkt}_{1,k}}$ for the aggregate market.

Same as the analysis on the real economy, we normalize the cumulative abnormal returns on month $t-1$ or day $t-20$ to 0: $CAR^s_{k,0} \equiv 0$. Each $CAR^s_{k,x}$ measures the x-day cumulative abnormal return: total returns in the downstream country's stock market in x days starting from 1 month (20 trading days) before the start of the disaster. Then we compute the mean of all disasters, $\overline{CAR}^s_x$, and their confidence intervals, to get the average impact of all climate disasters on downstream countries' sectoral stock indices' total returns in x days. To acquire the cumulative abnormal returns in the main upstream countries, we would simply replace the main downstream country k with the main upstream country j and redo the calculations for the main upstream countries.

Figures 7 shows that the cumulative abnormal returns in the aggregate stock market of main upstream and downstream countries are both about -0.5% and are significant at 95 percent confidence interval. The total loss from foreign climate disasters starts to stabilize about 40 trading days (2 months) after the disaster starts. These magnitudes of stock market losses in main downstream and upstream countries are comparable to the impact of a climate disaster on the home country's stock market (about -1%) documented in International Monetary Fund (2020). They are also comparable to the loss in main downstream and upstream GDP documented in Section 4.3.

Figure 7: Impact of Climate Disasters on Cumulative Abnormal Returns in Aggregate Stock Markets of Main Downstream and Upstream Countries

(a) Main Downstream (b) Main Upstream



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.

In main downstream and upstream countries, only the tradable sectors display negative and significant losses from foreign climate disasters. Figure C.2 plots the cumulative abnormal returns in sectoral stock market indices in the main downstream country. Figure C.3 plots the cumulative abnormal returns in sectoral stock market indices in the main upstream country. These figures show that the sectoral stock market responses to foreign disasters differ substantially across sectors. For example, the cumulative abnormal returns on chemical sector stocks are -0.8% in the main downstream country and -1% in the main upstream country, and those on automobile sector stocks are as large as -1.8% in the main downstream country and -1.5% in the main upstream country. Conversely, the media sector, the telecommunication sector, and other nontradable sectors not respond significantly to foreign climate disasters. Again this highlights that international trade is an important cross-border propagation mechanism for climate disasters.

Placebo Tests In Figure C.1, we show that in the median exporting and importing partner of the country that is directly hit by a climate disaster, neither the aggregate stock market nor sectoral stock indices are significantly affected by the disaster.

5.1 Cumulative Abnormal Returns and Downstream/Upstream Exposure Measures: Cross-sectional Analysis

We show that higher exposures to midstream climate disasters in the main downstream and main upstream countries lead to more negative cumulative abnormal returns in the stock markets of these countries. Furthermore, such negative impacts are more profound for the tradable sectors.

We first consider the regression specification for downstream countries. On the left hand side, we include the cumulative abnormal returns in downstream country k sector s stocks, $CAR^s_{k,100}$, which we compute in Section 5. Same as Section 3.2.2, we capture the downstream country's exposure to the midstream climate disaster with $\frac{Damage_{i,d} \times S_{k,i,\bar{y}}}{GDP_{k,\bar{y}}}$. We first examine this impact sector by sector:

$$CAR^s_{k,100} = \alpha^s_1 \frac{Damage_{i,d} \times S_{k,i,\bar{y}}}{GDP_{k,\bar{y}}} + \delta^s_k + \gamma^s_y + \epsilon^s_d. \tag{10}$$

For each sector, this regression is run on the level of disasters. For each disaster d, we uniquely identify the country that is hit by the disaster, i, the main downstream country, k, the year that the disaster hits, y, and the previous year for which we get the downstream GDP, $GDP_{k,\bar{y}}$, and the output share, $S_{k,i,\bar{y}}$. The cross-disaster variations identify α^s_1, which govern how downstream exposures affect sector s stock market returns in the downstream country.

Table 7 shows that in downstream countries, exposures to midstream climate disasters lead to significant declines in stock market returns on the aggregate level and for tradable sectors. A 0.1% increase in the downstream exposure measure leads to a 5.9% decline in downstream stock market total returns in 4 months. The impact on most tradable sectors in the downstream country – automobile, basic materials, chemicals, food and beverages, food producers, industrial goods, and industrial producers – is negative and significant. For example, a 0.1% increase in the downstream exposure measure leads to a more than 10% decline in the stock market valuations in downstream automobile and chemical sectors. Conversely, the cumulative abnormal returns in most non-tradable sectors are not significantly affected by the extent that downstream countries are exposed to midstream disasters.

Similarly, we use the following specification to investigate the impact of upstream exposure measures on sectoral stock market returns in the main upstream countries:

$$CAR^s_{j,100} = \alpha^s_1 \frac{Damage_{i,d} \times \pi_{i,j,\bar{y}}}{GDP_{j,\bar{y}}} + \delta^s_j + \gamma^s_y + \epsilon^s_d, \tag{11}$$

where, as in Section 5, $CAR^s_{j,100}$ denotes the cumulative abnormal returns in sector s, upstream country j, due to disaster d. As in Section 3.2.2, $\frac{Damage_{i,d} \times S_{k,i,\bar{y}}}{GDP_{k,\bar{y}}}$ denotes the upstream exposure measure to midstream climate disasters.

Table 8 shows that similar to the downstream countries, in upstream countries, exposures to midstream climate disasters lead to significant declines in stock market returns in the aggregate market and tradable sectors. A 0.1% increase in upstream exposures decreases returns in upstream aggregate market, automobile sector, and chemical sector by 3.7%, 13.3%, and 11.6%, respectively. Most non-tradable sectors in upstream countries do not respond significantly to midstream climate disasters.

Sector Tradability and Cross-border Spillovers of Climate Disasters We show that in the downstream countries, sectors that are more tradable respond more strongly to midstream climate disasters. We consider a pooled regression of all climate disasters and sectors, in which we interact the downstream exposure measure with how tradable a sector is (in terms of importing):

$$CAR^s_{k,100} = \mu \frac{Damage_{i,d} \times S_{k,i,\bar{y}}}{GDP_{k,\bar{y}}} + \lambda \frac{Damage_{i,d} \times S_{k,i,\bar{y}}}{GDP_{k,\bar{y}}} \times TDIM^s + \gamma_y + \zeta^s + \epsilon^s_d, \tag{12}$$

where $TDIM^s$ equals sector s total imports divided by the sector's total expenditure on the world level. We control for the upstream country fixed effect, the year fixed effect, and the sector fixed effect which captures the level effect that tradability has on the cumulative returns.

Column 1 of Table 9 shows that for an average sector in the main downstream country, the stock market returns are negatively impacted by the downstream exposures to midstream climate disasters. A 0.1% increase in the exposure measure leads to 4.7% decline in an average downstream sector returns.

Column 3 of the same table shows that more tradable sectors in downstream countries respond more to their exposures to midstream climate disasters. As long as we include the interaction between downstream exposure measure and importing tradability, the level effect of the downstream exposure measure becomes insignificant. Meanwhile, the interaction between the downstream exposure measure and the importing tradability is negative and significant.

To investigate whether upstream tradable sectors respond more to midstream climate disasters, we consider the following specification:

$$CAR^s_{k,100} = \mu \frac{Damage_{i,d} \times \pi_{i,j,\bar{y}}}{GDP_{j,\bar{y}}} + \lambda \frac{Damage_{i,d} \times \pi_{i,j,\bar{y}}}{GDP_{j,\bar{y}}} \times TDEX^s + \gamma_y + \zeta^s + \epsilon^s_d. \quad (13)$$

where $TDEX^s$ equals sector s total exports divided by the sector's total expenditure on the world level. We control for the upstream country fixed effect, the year fixed effect, and the sector fixed effect.

Similar to the findings for downstream sectors, Column 2 of Table 9 shows that for an average sector in the main upstream country, a 0.1% increase in the exposure to midstream climate disaster leads to 3.3% decline in an average upstream sector returns. Column 4 shows that, if we include the interaction between the upstream exposure measure with the upstream sector's tradability, the level effect of the exposure measure becomes insignificant, and the interaction term is significantly negative. These findings confirm that the negative cross-border spillover effects on upstream sectors are also entirely driven by the tradable sectors.

5.2 Climate Disaster Spillovers and the Financial Sector

International Monetary Fund (2020) shows 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. Insurance penetration and sovereign rating upgrade improve the financial sector valuations, holding fixed the magnitude of the disasters.

Table 7: Cross-sectional Analysis: Downstream Exposure Measure and Sectoral Cumulative Abnormal Returns

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	MRKTS	AUTMB	BANKS	BMATR	BRESR	CHMCL	CNSTM
Downstream Exposure	-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
Δsd	-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
Downstream Exposure	-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
Δsd	-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
Downstream Exposure	-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
Δsd	-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		
Downstream Exposure	-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		
Δsd	-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

Description: 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 Δsd 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.

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 show that the financial sectors in countries that have (1) lower trade insurance and (2) more risks in the financial system are more vulnerable to the cross-border spillover effects of climate disasters. We measure the trade insurance with the degree of international factoring (the ratio of factoring volume to GDP) – a form of

Table 8: Cross-sectional Analysis: Upstream Exposure Measure and Sectoral Cumulative Abnormal Returns

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	MRKTS	AUTMB	BANKS	BMATR	BRESR	CHMCL	CNSTM
Upstream Exposure	-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
Δsd	-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
Upstream Exposure	-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
Δsd	-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
Upstream Exposure	-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
Δsd	-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
Upstream Exposure	-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
Δsd	-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

Description: 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 Δsd 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.

protection for domestic traders – and we measure financial system risks with the standard metrics – banking sector capitalization (the ratio of the bank regulatory capital-to-risk-weighted assets).[34] An increase in domestic trader protection should lead to smaller

[34]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,

Table 9: Cross-sectional Analysis: Sector Tradability, Exposures to Foreign Climate Disasters, and Sectoral Cumulative Abnormal Returns

VARIABLES	(1) CAR	(2) CAR	(3) CAR	(4) CAR
Downstream Exposure	-47.20**		-6.775	
	(22.43)		(30.80)	
Upstream Exposure		-32.67*		-8.964
		(16.37)		(16.07)
Downstream Exposure×Importing Tradability			-246.5***	
			(56.28)	
Upstream Exposure×Exporting Tradability				-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
Δsd	-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

Description: 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 Δsd 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 Δsd 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.

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 fi-

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 https://fci.nl/en/what-factoring. For the definition of the ratio of the bank regulatory capital-to-risk-weighted assets, see http://datahelp.imf.org/knowledgebase/articles/484367-in-financial-soundness-indicators-fsis-what-is.

nancial 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 investigate the roles of these institution variables in countries' financial sector vulnerability to foreign climate disasters, we consider the following specifications (to derive the specifications for upstream countries, replace the downstream country indicator k with upstream country indicator j, and replace the downstream exposure measure here with the upstream exposure measure, $\frac{Damage_{i,d} \times \pi_{i,j,\bar{y}}}{GDP_{j,\bar{y}}}$):

$$CAR^{FIN}_{k,40} = \alpha \frac{Damage_{i,d} \times S_{k,i,\bar{y}}}{GDP_{k,\bar{y}}} + \beta \text{ Factoring to GDP Ratio}_{k,\bar{y}} + \epsilon^s_d$$

$$CAR^{FIN}_{k,40} = \alpha \frac{Damage_{i,d} \times S_{k,i,\bar{y}}}{GDP_{k,\bar{y}}} + \beta \text{Bank Regulatory Capital to Asset Ratio}_{k,\bar{y}} + \epsilon^s_d$$

Columns 1 and 3 of Table C.3 show that 1% increase in total factoring volume to GDP ratio is associated with a 0.1% increase in the cumulative abnormal returns in downstream and upstream countries. According to Columns 2 and 4 of Table C.3, a 1% increase in the bank regulatory capital-to-risk-weighted assets ratio is associated with a 0.2% increase in the cumulative abnormal returns in downstream and upstream countries.

6 Foreign Long-term Climate Risks and Domestic Stock Market Valuations

Climate change leads to greater long-term risks of larger and more frequent climate disasters (BlackRock 2019, Woetzel et al. 2020). These 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. Forward-looking, rational investors expect that, when these risks realize, according to the findings in Section 5, the stock returns in the downstream and upstream countries will be negatively impacted. Therefore, they should price foreign climate risks into the valuation of their portfolios and decrease their valuations of the assets that are more affected by foreign climate risks.[35]

[35] For studies on how climate risks affect domestic financial market valuations, see International Monetary Fund (2020) for a review.

To measure foreign climate risk exposures, we slightly adapt the measure of exposure to climate disasters in upstream and downstream countries that we introduced in Section 3.2.2.

We capture a downstream country k's exposure to foreign climate risks in year y, by weighting the climate risks in all countries except k with the share of output that the other country sells to k:

$$D_{k,y} = \sum_{i \neq n} S_{k,i,y} R_i, \tag{14}$$

where R_i denotes the climate risks in country i. If $S_{k,i,y} = 0, \forall i \neq k$, no foreign country will sell to country n. In this case, $D_{k,y} = 0$, which implies that the downstream country k will not be exposed to any foreign climate risks at all. In our sample, all countries import from at least some foreign countries. Therefore, all countries are exposed to foreign climate risks through the downstream spillovers channel.

Similarly, we obtain an upstream country's foreign climate risk exposures as follows. In our sample, all countries are also exposed to foreign climate risks through the upstream spillovers channel:

$$U_{j,y} = \sum_{i \neq j} \pi_{i,j,y} R_i. \tag{15}$$

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. Both measures concern a long-term view for the climate and for the stock market performance. To implement the empirical strategy, we first employ the same methodology as in International Monetary Fund (2020) to take out the component in the P/E ratio that could be explained by the standard stock market valuation predictors. These include the interest rate ($r^f_{i,y}$, measured with the three-month government bond yield in the country of which the stock market we investigate), the sectoral expected future earnings ($EXPFE^s_{i,y}$, measured with the mean annual growth of earnings per share over the past five years), and the sectoral equity risk premium ($ERP^s_{i,y}$, measured with the standard deviation of annual growth of earnings per share over the past five years).[36]

We run the following regression sector by sector and we get the residual P/E ratio,

[36] To acquire the variables at the year level, we take the average of the monthly observations in the raw data.

$\widehat{RPE}^{s}_{i,y}$, which can not be explained by standard valuation metrics:

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

Next, we regress the residual P/E ratios on the upstream and downstream exposures to foreign risks with a pooled regression of all sectors:

$$\widehat{RPE}^{s}_{k,y} = \ b \times D_{k,y} + \phi_y + \zeta^s + \epsilon^s_{k,y}, \tag{16}$$

for downstream countries. For upstream countries, we use the following:

$$\widehat{RPE}^{s}_{j,y} = \ b \times U_{j,y} + \phi_y + \zeta^s + \epsilon^s_{j,y}, \tag{17}$$

Columns 1–2 of Table 10 show that country-sector level stock market P/E ratio is negatively associated with exposures to foreign climate risks in downstream and upstream countries. A one standard deviation increase in the exposures to foreign climate risks in downstream and upstream countries corresponds to about a 0.05 standard deviation decline in the P/E ratio. An inter-quartile increase in the exposures to foreign risks is associated with a reduction in the P/E ratio of about 3.0 for downstream countries and about 3.7 for upstream countries.

We show that international trade is 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). Columns 3–6 of Table 10 show that the P/E ratios of the industrial producers sector are strongly negatively correlated with upstream and downstream exposures to foreign climate risks. There is no significant correlation between the real estate sector's P/E ratios and foreign climate risks.

To formally test this hypothesis, we include the interaction between the importing tradability and the exposures to foreign climate risks in downstream countries as the regressor:[37]

$$\widehat{RPE}^{s}_{k,y} = b\, D_{k,y} \ + \ c\, TDIM^s \times D_{k,y} + \phi_y + \zeta^s + \epsilon^s_{k,y}. \tag{18}$$

[37]We also run a similar regression by replacing the exposures to 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 magnitudes of the coefficients.

Table 10: Association between exposure to foreign climate risks and home-country P/E ratio

VARIABLES	(1) Up pooled	(2) Down pooled	(3) Up INDUS	(4) Up RLEST	(5) Down INDUS	(6) Down RLEST	(7) Up 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) Down interaction	(9) Up placebo	(10) Down placebo	(11) Up placebo interaction	(12) Down placebo 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** (76.28)			51.45 (53.43)	31.64 (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

Description: 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 Δsd 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 Δsd 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.

We use the following specification for upstream countries:

$$\widehat{RPE}^{s}_{j,y} = b\,U_{j,y} \ + \ c\,TDEX^{s} \times U_{j,y} + \phi_y + \zeta^s + \epsilon^{s}_{j,y}. \tag{19}$$

Columns 7–8 of Table 10 show that, once the interaction term is introduced, the level effects of 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.[38]

We show that the negative association between the P/E ratios and exposures to foreign climate risks is not merely driven by openness to trade. We construct placebo upstream and downstream foreign risks by setting the placebo climate risks of all countries to $\frac{1}{N-1}$. The placebo foreign climate risks in downstream countries then equal the following:

$$\widetilde{D}_{k,y} = \frac{1}{N-1} \sum_{i \neq k} S_{k,i,y}.$$

$\widetilde{D}_{k,y}$ measures the average share of output that all foreign countries sell to country n. A larger $\widetilde{U}_{k,y}$ means country k is more important as a global exporting destination.

A country's placebo upstream foreign climate risks equal the following:

$$\widetilde{U}_{j,y} = \frac{1}{N-1} \sum_{i \neq j} \pi_{i,j,y}$$

$\widetilde{U}_{j,y}$ denotes the average expenditure share by all foreign countries that is spent on country i. A larger $\widetilde{U}_{j,y}$ means that country j is more important as a global importing origin. To conduct the placebo tests, we replace the actual exposure measures to foreign climate risks in Equations 16, 17, 18, and 19, with their corresponding placebo measures.

Columns 9–10 of Table 10 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, either. 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 risks.

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,

[38]For the sector at the 50th percentile of importing tradability (food and beverages), a one standard deviation increase in exposures to foreign risks in downstream countries 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 foreign risk exposures in upstream countries 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.

richer countries and the countries that have stronger current economic growth. To rule out these confounding channels, we replace climate risks R_i in Equations 16, 17, 18, and 19 with GDP, GDP per capita, GDP growth and per capita GDP growth in respective countries. In Appendix Table C.4, 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 prices.

In sum, in this section, we find significant correlations between exposures to foreign climate change risk and domestic stock valuations for tradable sectors. We do not find such correlation for non-tradable sectors. 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 well-being of many countries. The economic effect of climate disasters can be extremely devastating. Building resilience against climate shocks is important to enhancing macro-financial stability for individual countries. However, there is also a global aspect to climate risks: international trade and supply chain linkages can propagate climate risks across country borders.

In this paper, we find abundant and consistent evidence that climate disaster that happens to any country in the global supply chain can have significant macro-financial implications on other countries that trade intensively in the same network. These effects depend critically on whether the climate disasters hit ports and the sector compositions in the foreign partners of trade.

These results indicate that enhancing resilience against climate risks 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 support emerging market and developing economies to adapt to climate change. We call for international collaboration and collective policy actions.

While this paper focuses on the physical climate risk, the conceptual framework and analytical method could be applied to understand how climate transition risks (for example, a country's decarbonization efforts) affect the global economy. The framework is also readily applicable to the cross-border spillover effects of other crises, for example, COVID-19. The methodology may also be extended to study the spillovers of shocks with other forms of globalization, for example, multinational production, remittance, tourism, among others. 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. 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.

A Appendix for the Macroeconomic Impacts of Climate Disasters

A.1 Monthly GDP Estimation

To facilitate a interpolation algorithm to estimate a monthly GDP panel, we first obtain several macro indicators in monthly basis form Refinitive Datastream. The indicators are composed of a set of indexes related to economic activity, including industrial production index, industrial production manufacturing index, and employment persons. The assumption is that the gross domestic production should be reflected by the performance of economic activity. With higher industrial production index, we expect to see a higher gross production. Practically, we assume a linear relation between GDP and economic activity.

We proceed in the following steps to estimate a monthly GDP panel. We start with a raw GDP database we obtained from IFS and OECD statistics, which consists of quarterly and yearly GDP observations of 201 countries. Then, we merge the macro economic activity indexes to the raw panel by country and time. The monthly GDP is estimated by solving the functions given below. for a country i with GDP_{iq} in Quarter q:

$$\sum_{m \in q} GDP_{im} = GDP_{iq}$$
$$\frac{Index_m}{\sum_{m \in q} Index_m} = \frac{GDP_m}{\sum_{m \in q} GDP_m}$$

The estimation follows an algorithm which priories data availability. Hence, $Index_m$ is constructed with multiple macro indexes. That is, we first consider data entries where industrial production index is available for the observations. After estimating GDP in these months, we move on to the the remain entries and estimate GDP in months where another index, i.e. industrial manufacturing index, is available. We repeat this procedure for several times along the macro indexes we have to produce a comprehensive GDP monthly panel. Note that we mark an index as unavailable for a quarter if it has missing value for any month within the quarter. This guarantees that we only use one unique type of index to decompose GDP into monthly values for a given quarter.

A.2 Construction of the Stacked Date Set

Our main analysis consists of 430 large climate disasters, i.e. 430 events for the event study. Stacked DID requires us to estimate separate treatment effect event-by-event. To do so, we first construct 430 event-specific monthly panel. Then we stacked these datasets in relevant time and estimate the regression model featured in individual-event and time-event fixed effects.

For the event d-specific dataset, it includes the treated country and its best-matched clean control country for a 9-month panel by relevant time (t $= -4$, ..., 4). The disaster shock takes place at t $= 0$. Best-matched clean controls are identified through the following steps. First, we divide the datasets into two parts: the treatment group and the control group. The treatment group includes 9×430 observations around all disaster event. The control group include all remaining observations. Second, we estimate a propensity score for each observation, using previous year's population and GDP as dependent variable. Third, for each disaster d, say the disaster take place in year y_d, month m_d, we refine the control group to only keep observations at this exact same time, year y_d, month m_d. Them, among this refined control observations, we find the nearest neighbor of the treated country according to the propensity score.

Since now we have 430 treated-control pairs at $t = 0$, we complement the datasets by including all 9-month (t $= -4$, ..., 4) observations for each country. Thus we obtain the stacked data sets with $430 \times 2 \times 9$ observations.

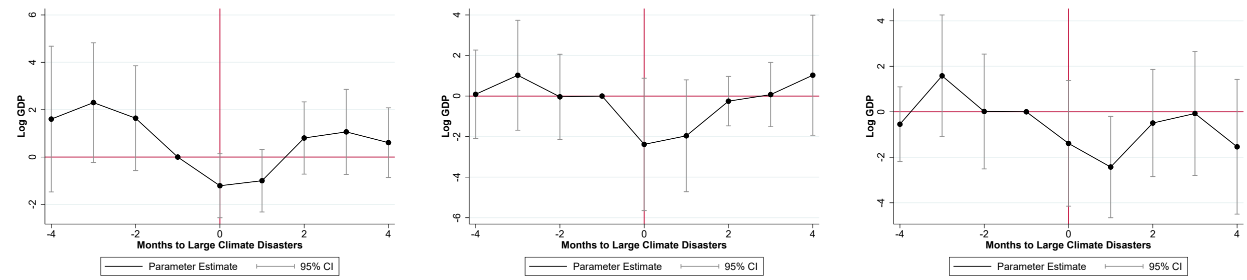
Figure A.1 shows the estimated disaster effect on midstream GDP for various matching variables. All 3 figures show negative coefficients for the first two months after the disaster shock, suggesting that the results are robust across different matching methods.

Figure A.1: **Disaster Effect on Midstream GDP: Different Matching Variables**

(a) Matched by GDP per capita and Population

(b) Matched by GDP per capita

(c) Matched by Population



Description: This figure contains the dynamics of the effect of a climate disaster on the log GDP of the country it directly hit using different matching variables. The x-axis contains the number of months to the disaster's starting date. GDP data is from the IMF and OECD statistics. We use the bilateral trade between a midstream country to its main upstream and main downstream country (as defined in Sector 3.2.2) as independent variable. The sample is composed of countries hit by a large climate disaster and their control pairs. We constrain the sample to the set of countries observed 4 months around the disaster shock. The vertical gray segments contain the 95% confidence interval. Standard errors are two-way clustered at the country-disaster level.

A.3 Additional Tables

Table A.1: **Summary Statistics**

Variable	N	Mean	St. Dev.	Min	Max
Panel A: Disaster Damage					
Affected Population (Million)	430	1.246	4.961	0.000	60.000
Affected Population Ratio (%)	430	2.396	6.245	0.000	71.525
Death Population (Thousand)	430	0.237	1.815	0.000	30.000
Death Ratio (%)	430	0.001	0.008	0.000	0.127
Monetary Damage (Million)	430	605.772	1,722.730	0.000	22,000
Damage Ratio (%)	430	0.587	2.186	0.000	31.403
Whether Affect Port (Indicator)	430	0.412	0.493	0	1
Whether Affected Airport (Indicator)	430	0.642	0.480	0	1
Panel B: Disaster-hit Country					
Advanced Economy (Indicator)	430	0.160	0.367	0	1
GDP (Billion)	430	469.528	1,643.988	0.143	18,715.050
Population (Million)	430	92.891	239.449	0.083	1,390.080
CPI (2011 = 100)	430	71.687	44.052	0.00000	432.913
Export (Billion)	430	82.311	256.952	0.012	2,262.559
Import (Billion)	430	79.871	228.830	0.075	2,241.454
Number of Port	430	5.453	7.306	0	48
Number of Airport	430	17.979	35.173	1	267
Panel C: Trade Structure					
Main Upstream as Advanced Economy (Indicator)	430	0.693	0.462	0	1
Main Downstream as Advanced Economy (Indicator)	430	0.812	0.391	0	1
Output Share to Main Downstream (%)	430	4.496	4.932	0.306	43.433
Expenditure Share on Main Upstream (%)	430	4.472	4.266	0.217	33.771
Upstream GDP (Billion)	430	4,885.645	4,793.811	13.565	18,569.100
Downstream GDP (Billion)	430	6,370.663	5,514.826	8.954	18,569.100
Upstream Exposure to Midstream Disaster (‰)	430	0.007	0.021	0.000	0.231
Downstream Exposure to Midstream Disaster (‰)	430	0.005	0.017	0.000	0.216

Description: This table summarises basic information of large climate disasters in our sample. Panel A presents the summary of disaster damage. Panel B presents the summary of macroeconomic variables in disaster-hit home country. Panel C presents the summary of trade structure variables describing the trade linkage between home country and its main trade partner. All variables in Panel B and Panel C are yearly observations observed in the year before the disaster.

Table A.2: **Impact of Climate Disasters on Midstream Production, Price and Trade: Port Interaction Specification**

VARIABLES	(1) Log GDP	(2) Log CPI	(3) Log Export	(4) Log Import	(5) Log Export to Main Downstream	(6) Log Import from Main Upstream
Damage Ratio	-0.621	0.255	-1.138	1.652**	0.347	1.642
	(1.184)	(0.362)	(1.110)	(0.688)	(1.165)	(1.252)
Affect Port	-0.00830	0.00128	-0.00410	-0.0126	-0.00398	-0.0408**
	(0.0128)	(0.00724)	(0.0137)	(0.0124)	(0.0396)	(0.0178)
Damage Ratio $\times$ Affect Port	-0.271	-0.102	0.181	-1.781**	-2.152*	-2.264*
	(1.215)	(0.366)	(1.156)	(0.689)	(1.195)	(1.267)
Observations	7,740	7,740	7,740	7,740	7,740	7,740
Cou. X Dis. FE	Yes	Yes	Yes	Yes	Yes	Yes
Time X Dis. FE	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Dis.	Dis.	Dis.	Dis.	Dis.	Dis.
Mean Dep. Var	8.416	4.091	20.68	20.89	19.09	19.26
R^2	0.190	0.115	0.193	0.148	0.513	0.280

Description: This table presents the estimated parameters of model 2. The sample is composed of countries hit by a large climate disaster and their control pairs. We constrain the sample to the set of countries observed 4 months around the disaster shock. "Damage Ratio" is the monetary loss caused by the disaster divided by home country's yearly GDP. "Affect Port" is a indicator which equals 1 if at least one port is affected by the disaster. Log GDP is the log of gross domestic production. Log CPI is the log of the CPI plus 1. Log Export is the log of aggregate export. Log Import is the log of aggregate import. Log Export to Main Downstream is the log of export from midstream country to its main downstream country (See Section 3.2.2). Log Import from Main Upstream is the log of midstream's import from its main upstream country (See Section 3.2.2). Standard errors are two-way clustered at the country-disaster level. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A.3: **Impact of Climate Disasters on Foreign Country's Production, Price and Trade: Port Interaction Specification**

VARIABLES	(1) Log Downstream GDP	(2) Log Downstream CPI	(3) Log Downstream Import	(4) Log Upstream GDP	(5) Log Upstream CPI	(6) Log Upstream Export
Exposure to Foreign Disaster	-172.1	37.27	43.48	-15.77	-73.81	220.3
	(202.4)	(66.28)	(276.5)	(177.4)	(53.02)	(258.5)
Affect Port	0.00394	-0.00307	-0.00212	0.00291	-0.00700**	-0.00777
	(0.00661)	(0.00209)	(0.00708)	(0.00658)	(0.00289)	(0.00618)
Exposure to Foreign Disaster	-733.4*	15.21	-77.59	-507.0*	152.0**	-292.3
$\times$ Affect Port	(422.2)	(77.42)	(497.1)	(272.8)	(57.36)	(315.9)
Observations	7,740	7,740	7,740	7,740	7,740	7,740
Cou. X Dis. FE	Yes	Yes	Yes	Yes	Yes	Yes
Time X Dis. FE	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Dis.	Dis.	Dis.	Dis.	Dis.	Dis.
Mean Dep. Var	12.16	4.422	24.24	11.96	4.412	24.04
R^2	0.0842	0.0255	0.0802	0.0747	0.0269	0.0574

Description: The sample is composed of midstream country's main trade partners and their control pairs. We constrain the sample to the set of countries observed 4 months around the disaster shock. "Exposure to Foreign Disaster" is the monetary loss in the midstream country divided by downstream or upstream country's yearly GDP $\times$ output share or expenditure share of the home country on the trade partners. "Affect Port" is a indicator which equals 1 if at least one port is affected by the disaster. Log Downstream GDP is the log of downstream gross domestic output. Log Downstream CPI is the log of downstream CPI plus 1. Log Downstream Import is the log of downstream country's aggregate import. Log Upstream GDP is the log of upstream gross domestic output. Log Upstream CPI is the log of upstream CPI plus 1. Log Upstream Export is the log of upstream country's aggregate export. Standard errors are two-way clustered at the country-disaster level. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A.4: **Impact of Climate Disasters on Foreign Country's Production: Regarding to Emerging Market**

VARIABLES	(1) Log Downstream GDP	(2) Log Downstream GDP	(3) Log Upstream GDP	(4) Log Upstream GDP
Exposure to Foreign Disaster	-492.4	-526.5	-359.3	-252.3
	(387.5)	(356.5)	(249.2)	(232.6)
Emerging Market	0.00656		0.00427	
	(0.00786)		(0.00732)	
Exposure to Foreign Disaster × Emerging Market	-4,175		-385.0	
	(3,051)		(430.8)	
Downstream Emerging Market		-0.00682		
		(0.0271)		
Exposure to Foreign Disaster × Downstream Emerging Market		-9,471*		
		(5,379)		
Upstream Emerging Market				0.0121
				(0.0149)
Exposure to Foreign Disaster × Upstream Emerging Market				-979.6***
				(308.4)
Observations	3,186	3,186	3,186	3,186
Cou. X Dis. FE	Yes	Yes	Yes	Yes
Time X Dis. FE	Yes	Yes	Yes	Yes
Cluster	Dis.	Dis.	Dis.	Dis.
Mean Dep. Var	12.16	12.16	11.96	11.96
R^2	0.0758	0.0755	0.0703	0.0702

Description: This table presents the estimated parameters of model 6 and 4, additionally including a set of dummy variables indicating whether the disaster-hit country or the trade partners are classified as emerging markets. The sample is composed of midstream country's main trade partners and their control pairs. We constrain the sample to the set of countries observed 4 months around the disaster shock. Only disasters that affect at least one local port are included in this sample. "Exposure to Foreign Disaster" is the monetary loss in the midstream country divided by downstream or upstream country's yearly GDP × output share or expenditure share of the home country on the trade partners. "Emerging Market" is an indicator which equals 1 if the disaster hit an emerging market. "Downstream Emerging Market" is an indicator which equals 1 if the main downstream of the disaster-hit country is an emerging market. "Upstream Emerging Market" is an indicator which equals 1 if the main upstream of the disaster-hit country is an emerging market. Log GDP is the log of gross domestic production. Standard errors are two-way clustered at the country-disaster level. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A.5: **Gravity Effect on Disaster Spillovers**

VARIABLES	(1) Log Downstream GDP	(2) Log Downstream GDP	(3) Log Downstream GDP	(4) Log Upstream GDP	(5) Log Upstream GDP	(6) Log Upstream GDP
Treated	-0.0879*	0.00294	-0.0706	-0.0388	-0.00432	-0.0619
	(0.0484)	(0.00661)	(0.0455)	(0.0451)	(0.00763)	(0.0521)
Treated×Log Distance	0.0103*		0.00847	0.00467		0.00699
	(0.00560)		(0.00525)	(0.00561)		(0.00624)
Treated×Contiguity		-0.0267	-0.0145		0.0213	0.0262
		(0.0264)	(0.0275)		(0.0178)	(0.0180)
Observations	3,186	3,186	3,186	3,186	3,186	3,186
Cou. X Dis. FE	Yes	Yes	Yes	Yes	Yes	Yes
Time X Dis. FE	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Dis.	Dis.	Dis.	Dis.	Dis.	Dis.
Mean Dep. Var	12.16	12.16	12.16	11.96	11.96	11.96
R^2	0.0759	0.0760	0.0760	0.0704	0.0703	0.0703

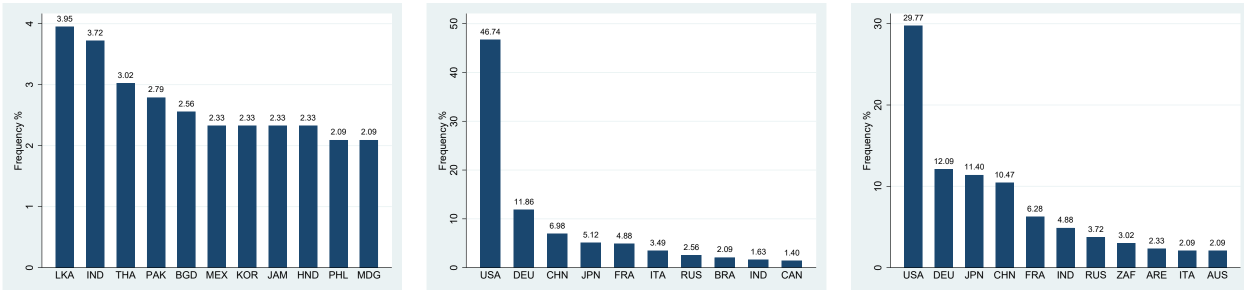
Description: This table presents the size of disaster spillovers in regarding to gravity variables. The sample is composed of midstream country's main trade partners and their control pairs. We constrain the sample to the set of countries observed 4 months around the disaster shock. Only disasters that affect at least one local port are included in this sample. "Exposure to Foreign Disaster" is the monetary loss in the midstream country divided by downstream or upstream country's yearly GDP × output share or expenditure share of the home country on the trade partners. "log(distance)" is the log of weighted distance between a downstream/upstream country and the disaster-hit home country. "Contiguity" is an indicator which equals 1 if the downstream/upstream country shares a common border with the disaster-hit home country. Log GDP is the log of gross domestic production. Standard errors are two-way clustered at the country-disaster level. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Figure A.2: **Distribution of Disaster-hit Countries and Main Trade Partners**

(a) Most Frequent Disaster-hit country

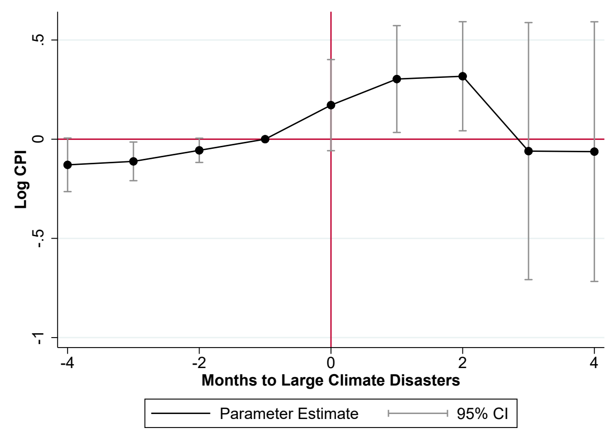
(b) Most Frequent Main Downstream Country

(c) Most Frequent Main Upstream Country



Description: Figure (a) shows the top 10 countries most frequently hit by a large climate disaster in our sample. Figure (b) shows the top 10 countries that disaster-hit countries most frequently export most to. Figure (c) shows the top 10 countries that disaster-hit countries most frequently import most from.

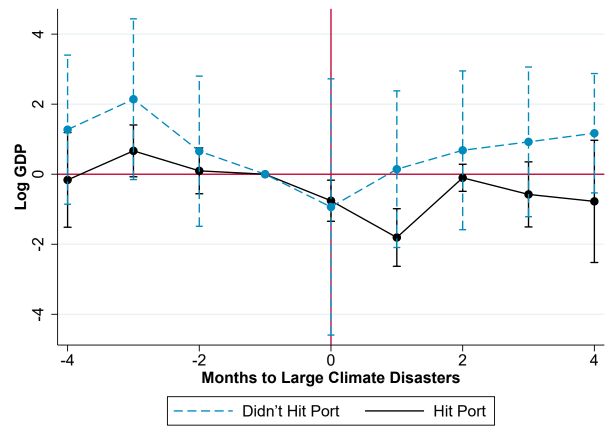
Figure A.3: **Impact of Climate Disasters on Midstream Price**



Description: This figure contains the coefficients of the effect of a climate disaster on log (CPI plus 1) of the country it directly hit using the stacked event-study model 1. The x-axis contains the number of months to the disaster's starting date. CPI data is from the IMF statistics. The sample is composed of countries hit by a large climate disaster and their control pairs. We constrain the sample to the set of countries observed 4 months around the disaster shock. The vertical gray segments contain the 95% confidence interval. Standard errors are two-way clustered at the country-disaster level.

A.4 Additional Figures

Figure A.4: **Impact of Climate Disasters on Midstream Production by Whether They Hit Port**

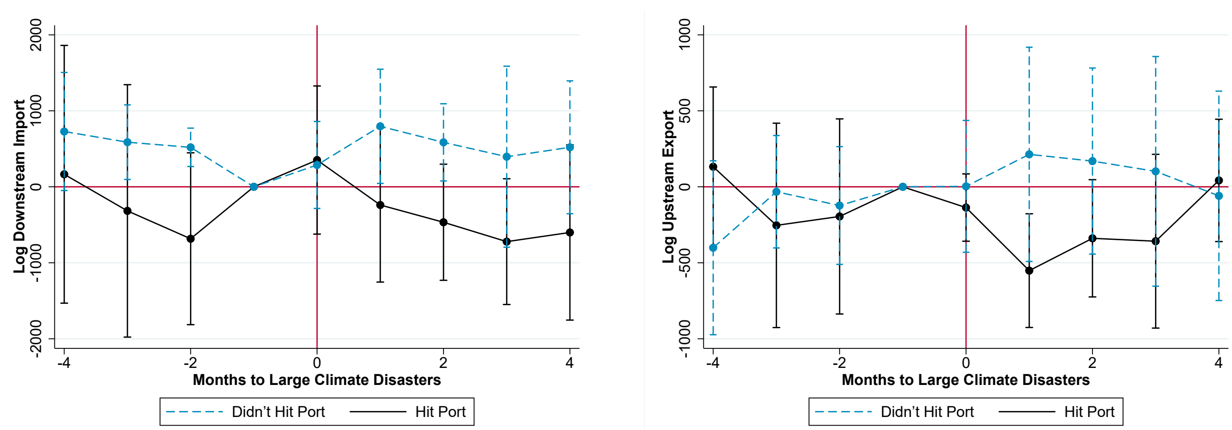


Description: This figure contains the coefficients of the effect of a climate disaster on log GDP of the country it directly hit using the stacked event-study model 1. The x-axis contains the number of months to the disaster's starting date. GDP data is obtained and estimated based on IMF and OECD statistics. The sample is composed of countries hit by a large climate disaster and their control pairs. We constrain the sample to the set of countries observed 4 months around the disaster shock. The vertical gray segments contain the 95% confidence interval. Standard errors are two-way clustered at the country-disaster level.

Figure A.5: **Impact of Climate Disasters on Downstream and Upstream Trade by Whether They Hit a Port**

(a) Downstream Total Imports

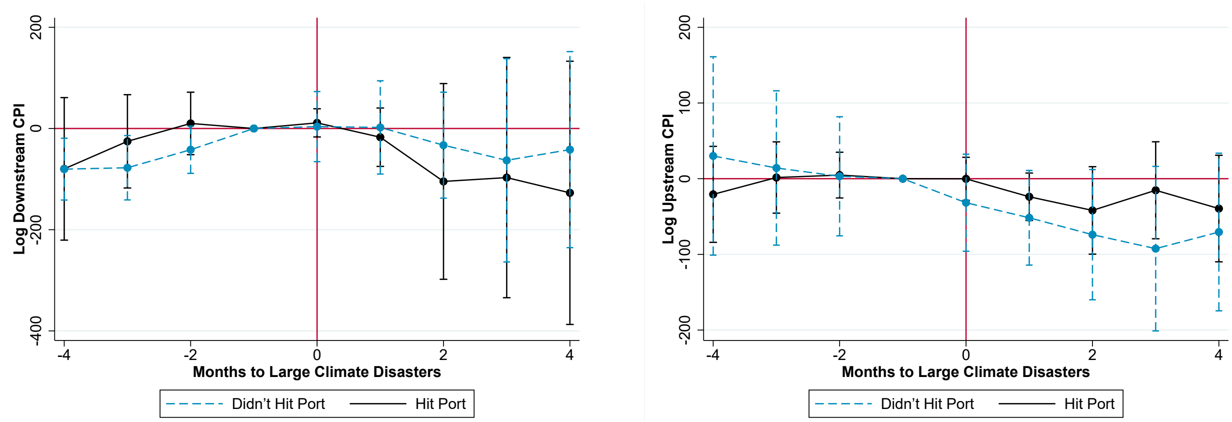
(b) Upstream Total Exports



Description: This figure contains the coefficients of the effect of a climate disaster on the log import and export of the midstream country's main downward and upward trade partners using the stacked event-study model 3 and 5. The x-axis contains the number of months to the disaster's starting date. Trade data is from the IMF DOT statistics. The sample is composed of midstream country's main trade partners and their control pairs. We constrain the sample to the set of countries observed 4 months around the disaster shock. The sample is split into 2 sub-samples. One contains disasters that affect at least one local port, the other contains disasters that don't hit any port. The black curve and vertical segments contain coefficients and 95% CI based on the "Hit Port" sub-sample. The blue dashed curve and vertical segments contain coefficients and 95% CI based on the "Didn't Hit Port" sub-sample. Standard errors are two-way clustered at the country-disaster level.

Figure A.6: **Impact of Climate Disasters on Downstream and Upstream Prices by Whether They Hit Port**

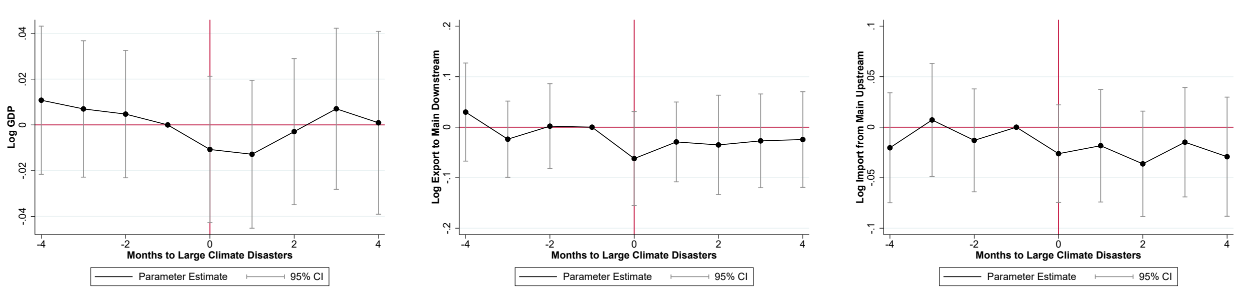
(a) Downstream Price (b) Upstream Price



Description: This figure contains the coefficients of the effect of a climate disaster on the log CPI of the midstream country's main downward and upward trade partners using the stacked event-study model 3 and 5. The x-axis contains the number of months to the disaster's starting date. CPI data is from the IMF statistics. The sample is composed of midstream country's main trade partners and their control pairs. We constrain the sample to the set of countries observed 4 months around the disaster shock. The sample is split into 2 sub-samples. One contains disasters that affect at least one local port, the other contains disasters that don't hit any port. The black curve and vertical segments contain coefficients and 95% CI based on the "Hit Port" sub-sample. The blue dashed curve and vertical segments contain coefficients and 95% CI based on the "Didn't Hit Port" sub-sample. Standard errors are two-way clustered at the country-disaster level.

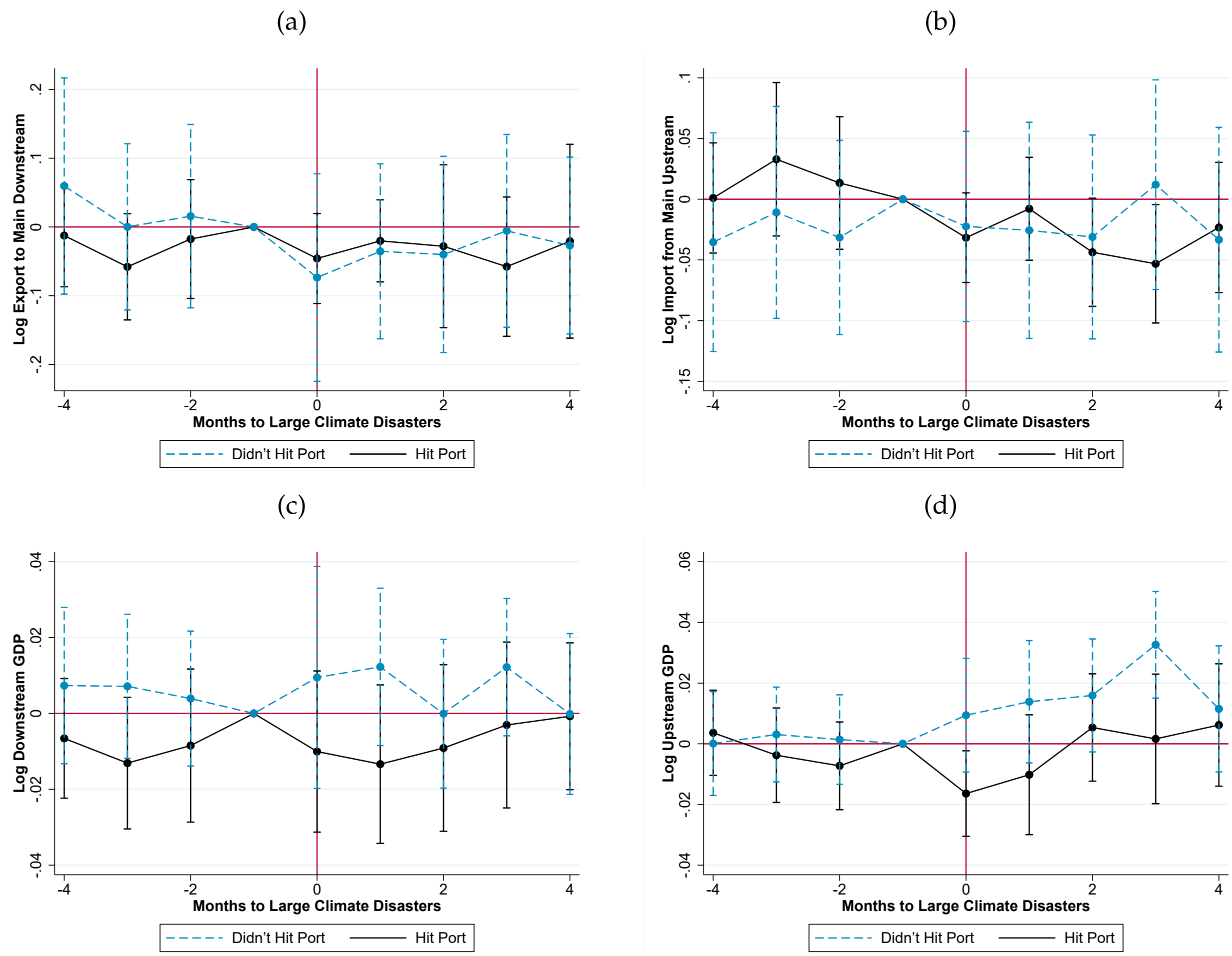
Figure A.7: **Impact of Climate Disasters on Midstream Production and Trade: Using dummy as independent variable**

(a) (b) (c)



Description: This figure contains the coefficients estimated from the stacked event-study model 1. We replace the independent variable with a dummy indicating whether a disaster has attached the country. The x-axis contains the number of months to the disaster's starting date. GDP data is obtained and estimated based on IMF and OECD statistics. Trade data is from the IMF DOT statistics. The sample is composed of countries hit by a large climate disaster and their control pairs. We constrain the sample to the set of countries observed 4 months around the disaster shock. The vertical gray segments contain the 95% confidence interval. Standard errors are two-way clustered at the country-disaster level.

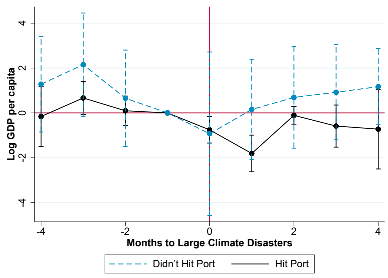
Figure A.8: **Disaster Spillover Effect: Using dummy as independent variable**



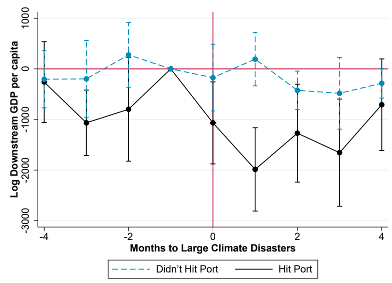
Description: This figure contains the coefficients estimated from the stacked event-study model 1, 3 and 5. We replace the independent variable with a dummy indicating whether a disaster has attached the country. The x-axis contains the number of months to the disaster's starting date. GDP data is obtained and estimated based on IMF and OECD statistics. Trade data is from the IMF DOT statistics. The sample is composed of countries hit by a large climate disaster and their control pairs. We constrain the sample to the set of countries observed 4 months around the disaster shock. The sample is split into 2 sub-samples. One contains disasters that affect at least one local port, the other contains disasters that don't hit any port. The black curve and vertical segments contain coefficients and 95% CI based on the "Hit Port" sub-sample. The blue dashed curve and vertical segments contain coefficients and 95% CI based on the "Didn't Hit Port" sub-sample. Standard errors are two-way clustered at the country-disaster level.

Figure A.9: **Impact of Climate Disasters on GDP per capita**

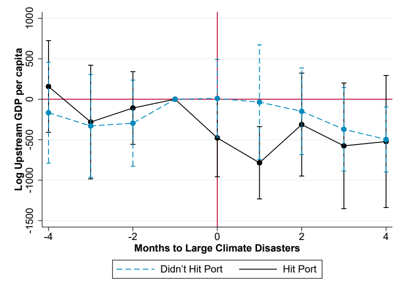
(a) Midstream



(b) Downstream



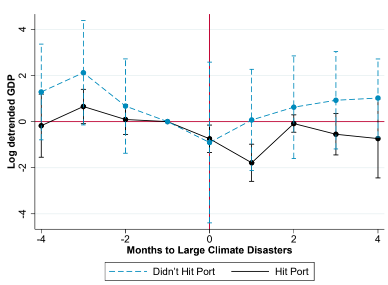
(c) Upstream



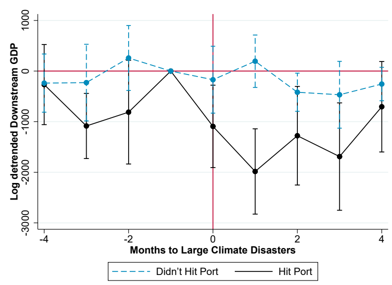
Description: This figure contains the coefficients estimated from the stacked event-study model 1, 3 and 5. The x-axis contains the number of months to the disaster's starting date. GDP data is obtained and estimated based on IMF and OECD statistics. The sample is composed of countries hit by a large climate disaster and their control pairs. We constrain the sample to the set of countries observed 4 months around the disaster shock. The sample is split into 2 sub-samples. One contains disasters that affect at least one local port, the other contains disasters that don't hit any port. The black curve and vertical segments contain coefficients and 95% CI based on the "Hit Port" sub-sample. The blue dashed curve and vertical segments contain coefficients and 95% CI based on the "Didn't Hit Port" sub-sample. Standard errors are two-way clustered at the country-disaster level.

Figure A.10: **Impact of Climate Disasters on GDP: Detrended and Seasonally Adjusted**

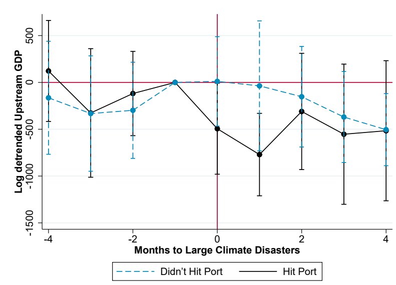
(a) Detrended Midstream



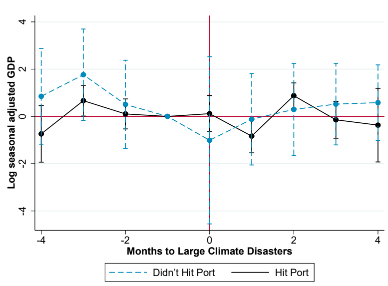
(b) Detrended Downstream



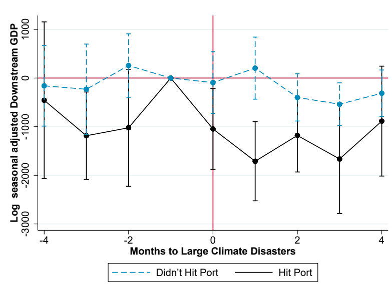
(c) Detrended Upstream



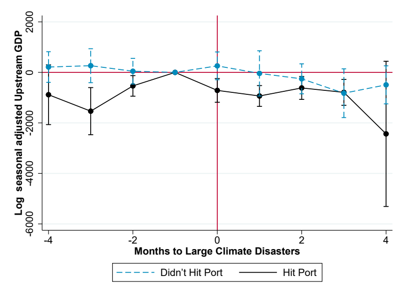
(d) Seasonally Adjusted Midstream



(e) Seasonally Adjusted Downstream



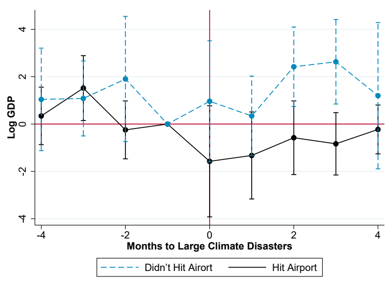
(f) Seasonally Adjusted Upstream



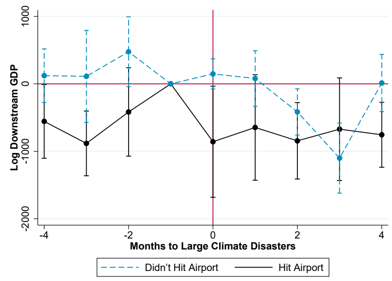
Description: This figure contains the coefficients estimated from the stacked event-study model 1, 3 and 5. The x-axis contains the number of months to the disaster's starting date. GDP data is obtained and estimated based on IMF and OECD statistics. Figure (a), (b), and (c) use linear-detrended GDP as dependent variable. Figure (d), (e), and (f) use seasonal adjusted GDP as dependent variable. The sample is composed of countries hit by a large climate disaster and their control pairs. We constrain the sample to the set of countries observed 4 months around the disaster shock. The sample is split into 2 sub-samples. One contains disasters that affect at least one local port, the other contains disasters that don't hit any port. The black curve and vertical segments contain coefficients and 95% CI based on the "Hit Port" sub-sample. The blue dashed curve and vertical segments contain coefficients and 95% CI based on the "Didn't Hit Port" sub-sample. Standard errors are two-way clustered at the country-disaster level.

Figure A.11: **Impact of Climate Disasters on GDP by Whether They Hit Airport**

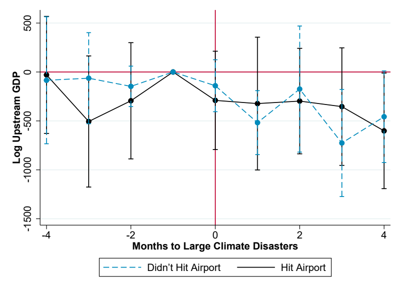
(a)



(b)



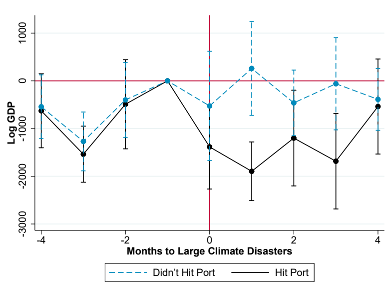
(c)



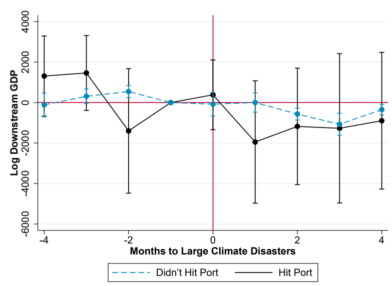
Description: This figure contains the coefficients estimated from the stacked event-study model 1. The x-axis contains the number of months to the disaster's starting date. GDP data is obtained and estimated based on IMF and OECD statistics. The sample is composed of countries hit by a large climate disaster and their control pairs. We constrain the sample to the set of countries observed 4 months around the disaster shock. The sample is split into 2 sub-samples. One contains disasters that affect at least one local airport, the other contains disasters that don't hit any airport. The black curve and vertical segments contain coefficients and 95% CI based on the "Hit Airport" sub-sample. The blue dashed curve and vertical segments contain coefficients and 95% CI based on the "Didn't Hit Airport" sub-sample. Standard errors are two-way clustered at the country-disaster level.

Figure A.12: **Impact of Climate Disasters on Foreign GDP by Whether the Main Downstream and the Main Upstream Countries Are the Same**

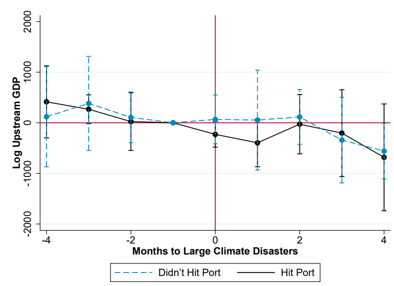
(a) Both Main Downstream and Main Upstream



(b) Only Main Downstream



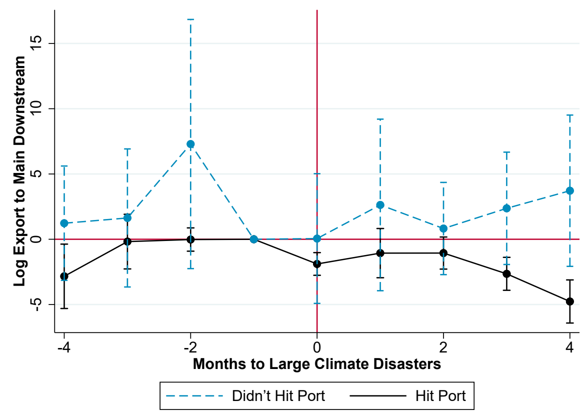
(c) Only Main Upstream



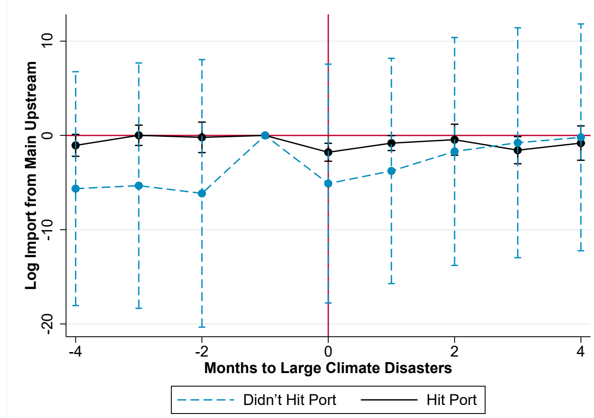
Description: This figure contains the coefficients estimated from the stacked event-study model 1. The x-axis contains the number of months to the disaster's starting date. GDP data is obtained and estimated based on IMF and OECD statistics. The sample is composed of countries hit by a large climate disaster and their control pairs. We constrain the sample to the set of countries observed 4 months around the disaster shock. Figure (a) uses a sample in which the main upstream and main downstream countries are the same for a midstream country. Figure (b) and (c) use a sample in which the main upstream country distinguishes from the main downstream for a midstream country. The samples are further split into 2 sub-samples. One contains disasters that affect at least one local airport, the other contains disasters that don't hit any airport. The black curve and vertical segments contain coefficients and 95% CI based on the "Hit Airport" sub-sample. The blue dashed curve and vertical segments contain coefficients and 95% CI based on the "Didn't Hit Airport" sub-sample. Standard errors are two-way clustered at the country-disaster level.

Figure A.13: **Impact of Climate Disasters on Bilateral Trade by Whether the Main Downstream Is Also the Main Upstream**

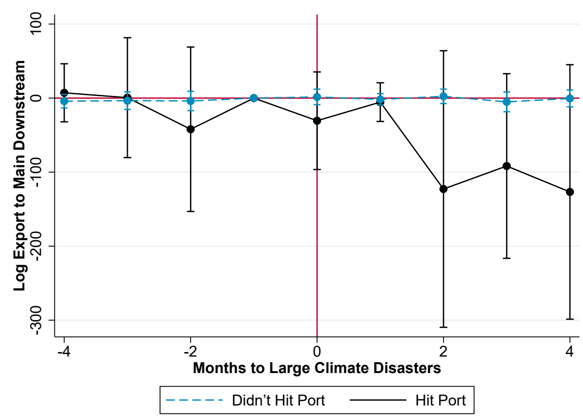
(a) Both Main Downstream and Main Upstream: Midstream Export to Downstream



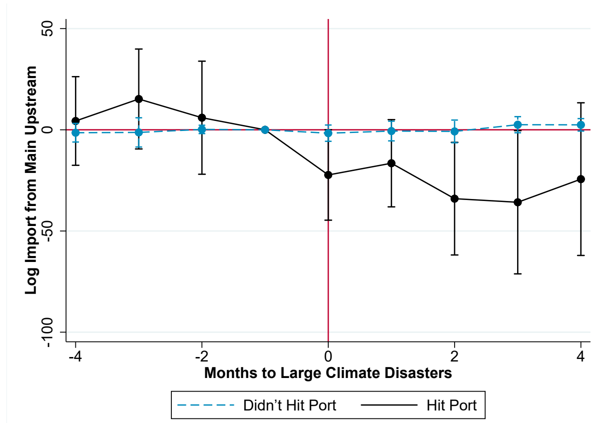
(b) Both Main Downstream and Main Upstream: Midstream Import from Upstream



(c) Only Main Downstream: Midstream Export to Downstream



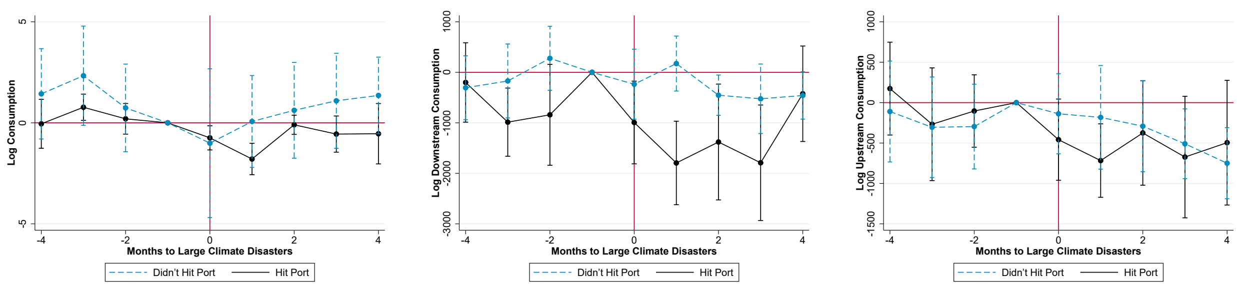
(d) Only Main Upstream: Midstream Import from Upstream



Description: This figure contains the coefficients estimated from the stacked event-study model 1. The x-axis contains the number of months to the disaster's starting date. Trade data is obtained from IMF DOT statistics. The sample is composed of countries hit by a large climate disaster and their control pairs. We constrain the sample to the set of countries observed 4 months around the disaster shock. Figure (a) and (b) use a sample in which the main upstream and main downstream countries are the same for a midstream country. Figure (c) and (d) use a sample in which the main upstream country distinguishes from the main downstream for a midstream country. The samples are further split into 2 sub-samples. One contains disasters that affect at least one local airport, the other contains disasters that don't hit any airport. The black curve and vertical segments contain coefficients and 95% CI based on the "Hit Airport" sub-sample. The blue dashed curve and vertical segments contain coefficients and 95% CI based on the "Didn't Hit Airport" sub-sample. Standard errors are two-way clustered at the country-disaster level.

Figure A.14: **Impact of Climate Disasters on Consumption by Whether They Hit Port**

(a) Downstream Consumption (b) Downstream Consumption (c) Upstream Consumption



Description: This figure contains the coefficients of the effect of a climate disaster on the log final consumption of the midstream country's main downward and upward trade partners using the stacked event-study model 2, 3 and 5. The x-axis contains the number of months to the disaster's starting date. Consumption data is obtained and estimated based on IMF statistics. The sample is composed of midstream country's main trade partners and their control pairs. We constrain the sample to the set of countries observed 4 months around the disaster shock. The sample is split into 2 sub-samples. One contains disasters that affect at least one local port, the other contains disasters that don't hit any port. The black curve and vertical segments contain coefficients and 95% CI based on the "Hit Port" sub-sample. The blue dashed curve and vertical segments contain coefficients and 95% CI based on the "Didn't Hit Port" sub-sample. Standard errors are two-way clustered at the country-disaster level.

B Contribution by Trade Disruption to the Cross-border Spillover Effect

In Appendix Section B, we show that it can be decomposed into a supply shock and a term that summarizes the trade disruption:

$$\text{dlog}(T_{k,i,t}) = \underbrace{\frac{\text{Damage}_{i,d} S_{k,i,\bar{y}}}{T_{i,k,\bar{y}}}}_{\text{Supply Shock}} + \underbrace{\text{dlog}(S_{i,k,t})}_{\text{Trade Disruption}}, \tag{B.1}$$

where, similar to Equation 3, the supply shock measures how the downstream country's imports from the midstream country is exposed to the disaster.[39] The trade disruption term measures how downstream country k's share in country i's output changes due to the climate disaster.

As shown in Section 4.4, climate disaster shifts midstream country's output and expenditure share. The change in these shares, may further enlarge or offset the loss in foreign productions through a weakened or strengthened trade linkage. Therefore, we propose that a foreign country can be affected in two ways after a climate disaster hits the home country: a demand or supply shock, and the disruption in trade. We establish the following equations to show how the aggregate effect can be decomposed into these two components. Take the disaster-hit midstream country i and its downstream partner k for instance:

$$\text{Sales from } i \text{ to } k = P_i Y_i S_{ki},$$

where S_{ik} is the trade flow divided by midstream i's aggregate output, namely the output share. Taking logs and derivatives on both side gives that:

$$\begin{aligned}
\text{dlog}(\text{Sales from } i \text{ to } k) &= \text{dlog}(P_i Y_i) + \text{dlog}(S_{ki}) \\
&= \frac{d(P_i Y_i) S_{ki}}{P_i Y_i S_{ki}} + \text{dlog}(S_{ki}) \\
&= \frac{\text{Damage}_i S_{ki}}{P_i Y_i S_{ki}} + \text{dlog}(S_{ki}) \\
&= \frac{\text{Damage}_i S_{ki}}{T_{ik}} + \text{dlog}(S_{ki}),
\end{aligned}$$

where $T_{ik} = P_i Y_i S_{ik}$ is the trade flow between country i and country k. A Higher S_{ik}

[39] In the data, we set $S_{k,i,\bar{y}}$ to its average value in the year prior to the climate disaster.

means midstream country i has more sales. If a trade disruption causes S_{ik} to fall, it means the hit country i is more reliant on domestic market, which will lead to a decline in sales from i to j. Furthermore, the downstream country k's production is:

$$P_k Y_k = \sum_{i=1}^{N} \text{Sales from } i \text{ to } k,$$

where Sales from i to k is k's domestic expenditure when $i = k$. Taking logs and derivatives on both side gives that:

$$\begin{aligned}
\text{dlog}(P_k Y_k) &= \sum_{i=1}^{N} \pi_{ki}\, \text{dlog}(\text{Sales from } i \text{ to } k) \\
&= \sum_{i=1}^{N} \pi_{ki} \frac{\text{Damage}_i S_{ki}}{T_{ik}} + \pi_{ki}\, \text{dlog}(S_{ki}) \\
&= \underbrace{\sum_{i=1}^{N} \frac{\text{Damage}_i S_{ki}}{P_k Y_k}}_{\text{supply shock}} + \underbrace{\pi_{ki}\, \text{dlog}(S_{ki})}_{\text{trade disruptions}},
\end{aligned}$$

where π_{ik} is the the trade flow divided by downstream k's aggregate output. Therefore, our decomposition is composed of two main procedures. First, we estimate the variation in trade shares explained by a climate disaster shock, denoting as $\widehat{d(S_{ik})}$. We fit the cross-sectional DID model 2 using the dynamic output share and expenditure share as dependent variable. Table 6 presents the first stage result of our decomposition. According to the result, we restrict the sample to disasters that have affected at least one port, since only these disasters have significant effect on trade with foreign countries.

Second, we construct the predicted change in trade, $\frac{\pi_{ik}}{S_{ik}}\widehat{d(S_{ik})}$, and use it as the measure for trade disruptions. Then we regress downstream GDP on supply shocks and trade disruptions by fitting the following model:

$$\begin{aligned}
y_{k,t} = &\underbrace{\beta_1 \times \mathbb{I}_{i,t}\{\text{After Climate Disaster}\} \times \frac{\text{Damage}_{i,d} S_{ik}}{\text{pre-GDP}_{k,d}}}_{A_1} \\
&+ \underbrace{\beta_2 \times \mathbb{I}_{i,t}\{\text{After Climate Disaster}\} \times \frac{\pi_{ik}}{S_{ik}}\widehat{d(S_{ik})}}_{A_2} + \alpha_{k,d} + \lambda_{t,d} + \epsilon_{k,d,t}
\end{aligned} \tag{B.2}$$

Similarly, we can substitute downstream k with upstream j to decompose the upward spillovers. Table B.1 shows the result for second stage regression. The contribution of supply shock is given by $\frac{\text{Cov}(A_1, A_1+A2)}{\text{Var}(A_1+A2)}$, while the contribution of trade disruption is $\frac{\text{Cov}(A_2, A_1+A2)}{\text{Var}(A_1+A2)}$. Therefore, the supply chain to downstream is disrupted but supply chain from upstream is strengthened. After a midstream country is hit by climate disaster, 97.14% of its main downstream's production loss is due to a reduction in foreign supply, while 2.86% of the loss is caused by trade disruption. Meanwhile, for the main upstream country, approximately one-sixth of the loss caused by the demand shock is offset by a strengthened trade linkage. For both upstream and downstream countries, the spillover effect is mainly driven by the supply or demand shock directly induced by the climate disaster.

Table B.1: **Second stage regression of decomposition**

VARIABLES	(1)	(2)	(3)	(4)
	Log Downstream GDP		Log Upstream GDP	
	Coefficients	Contribution	Coefficients	Contribution
Supply/Demand Shock	-827.8**	97.6%	-848.5**	146.6%
	(383.8)		(399.7)	
Trade Openness	0.299***	2.4%	87.36*	-46.6%
	(0.0151)		(46.36)	
Observations	3,186		3,186	
Mean Dep. Var	12.36		12.21	
R^2	0.0759		0.0703	

Description: This table presents the estimated parameters of model B.2. The sample is composed of midstream country's main trade partners and their control pairs. We constrain the sample to the set of countries observed 4 months around the disaster shock. Only disasters that affect at least one local port are included in this sample. Standard errors are two-way clustered at the country-disaster level. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

C Appendix for Stock Market Analysis

C.1 Additional Tables

Table C.1: 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 C.2: 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

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

Table C.3: Cross-sectional analysis: association between country institutional factors and cumulative abnormal return in the financial sector

VARIABLES	(1) CAR40	(2) CAR40	(3) CAR40	(4) 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

Description: 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 C.4: 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

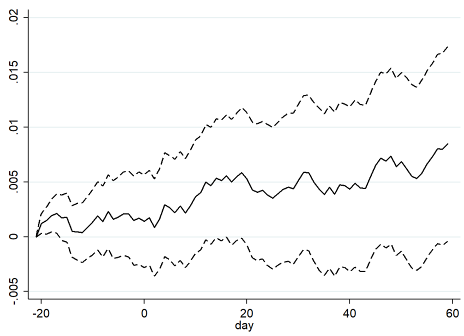
Robust standard error in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Description: 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.

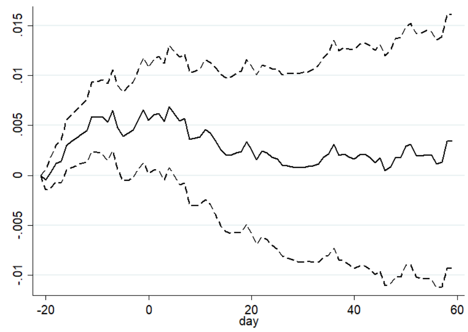
C.2 Additional Figures

Figure C.1: Climate disasters do not significantly affect the stock market returns in non-major trade partners of the countries hit by climate disasters

(a) Placebo, Main Downstream



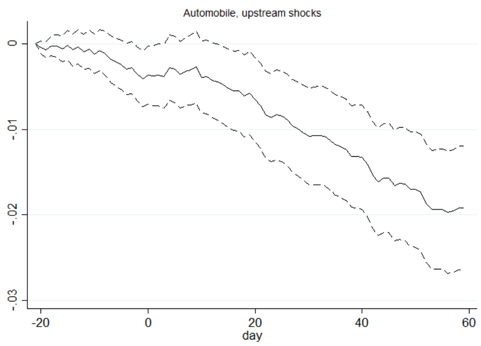
(b) Placebo, Main Upstream



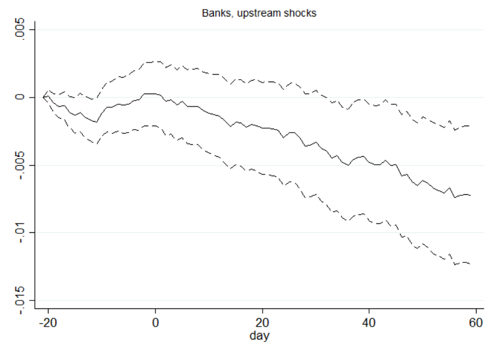
The figures plot the cumulative abnormal returns in the market indexes of the 35th largest exporting destination of the upstream disaster-hit country and the 35th largest importing origin of the downstream disaster-hit country from 20 days before the disaster to 60 days after the disaster.

Figure C.2: Sector-level stock market returns in the main exporting destination of upstream disaster-hit country

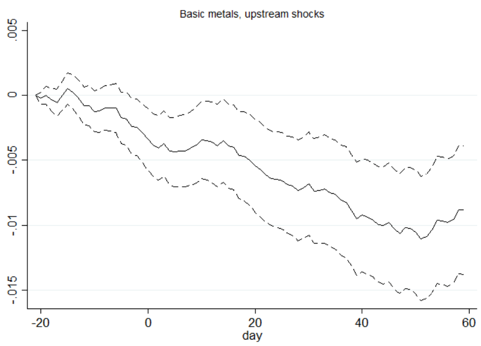
(a) Automobiles and parts



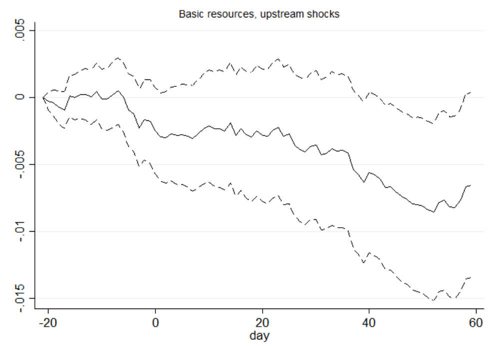
(b) Banks



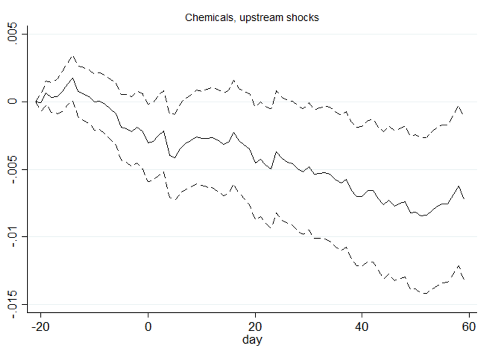
(c) Basic materials



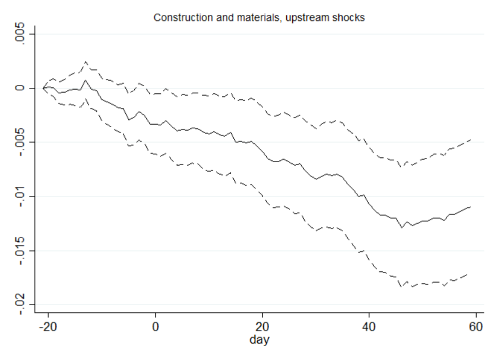
(d) Basic resources



(e) Chemicals

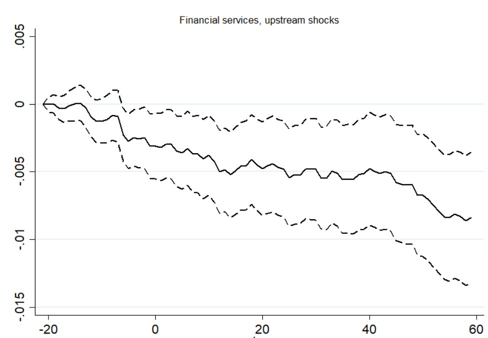


(f) Construction and materials

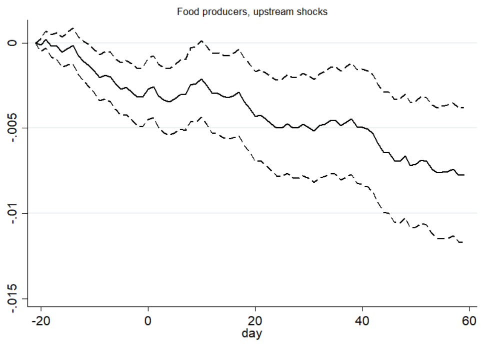


(g) Food and beverages

(h) Financial services



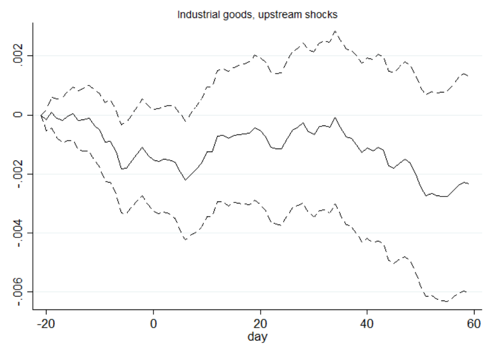
(i) Food producers



(j) Household goods and home construction

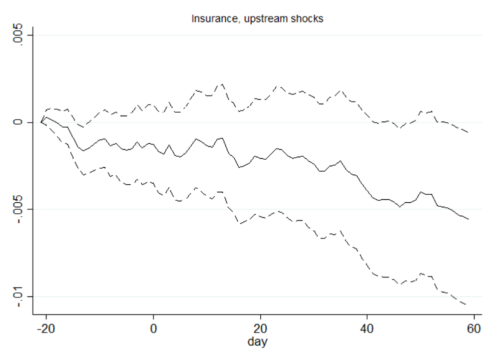
(k) Utilities

(l) Industrial goods

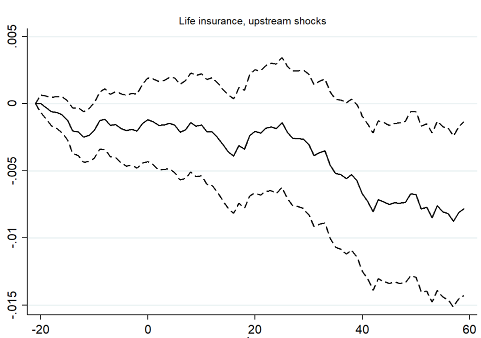


(m) Industrial producers

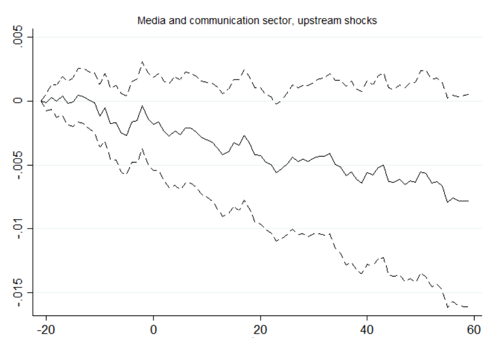
(n) Insurance



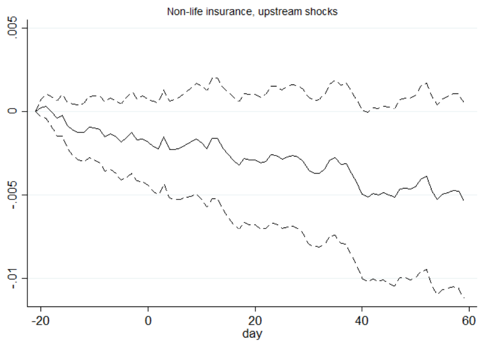
(o) Life insurance



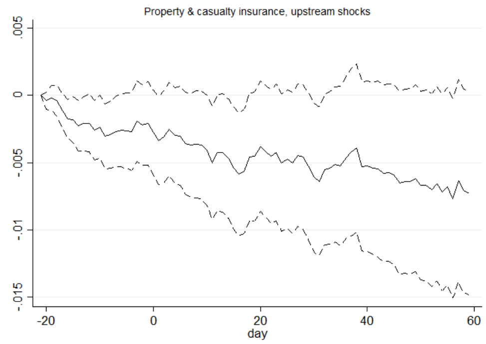
(p) Media and communication



(q) Non-life insurance



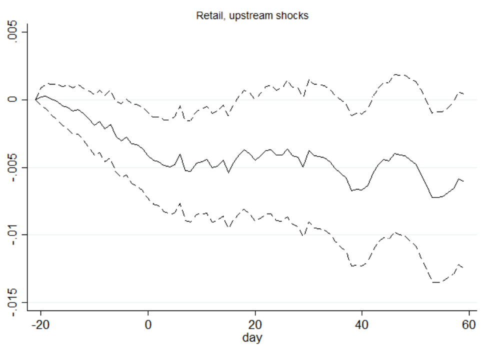
(r) Property and casualty insurance



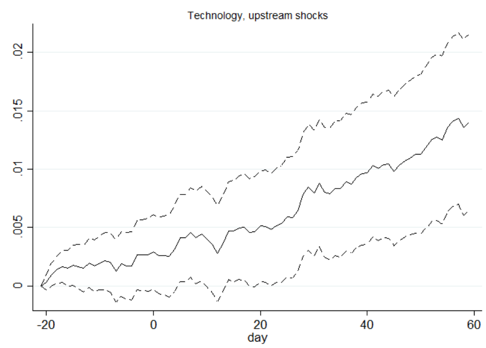
(s) Reinsurance

(t) Real estate

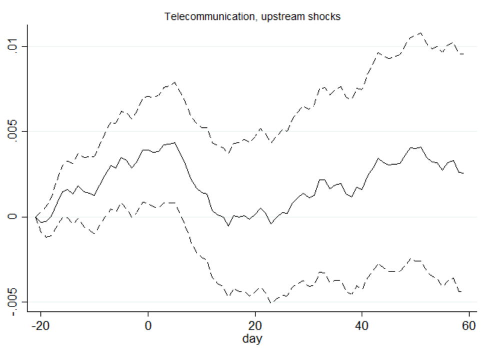
(u) Retail



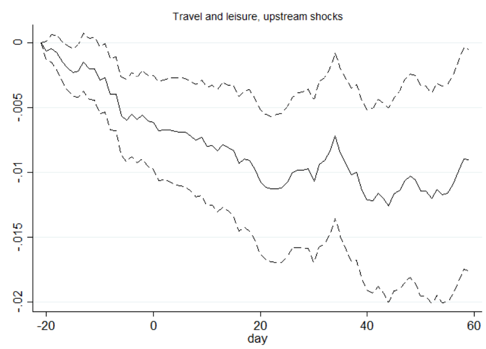
(v) Technology



(w) Telecommunications



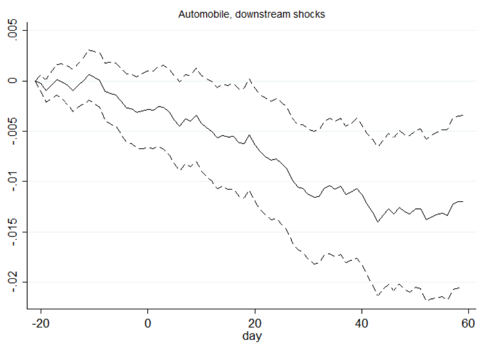
(x) Travel and leisure



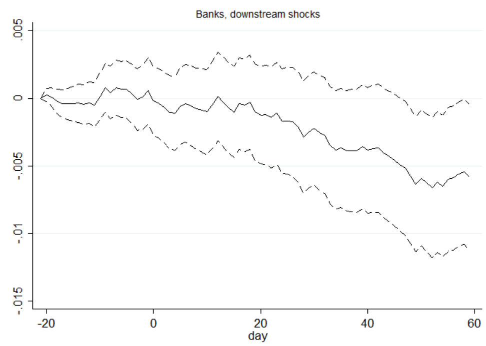
The figures plot cumulative abnormal returns in sector-level stock indexes in the main exporting destination of upstream disaster-hit country from 20 days before the upstream disaster to 60 days after the upstream disaster.

Figure C.3: Sector-level stock market returns in the main importing origin of downstream disaster-hit country

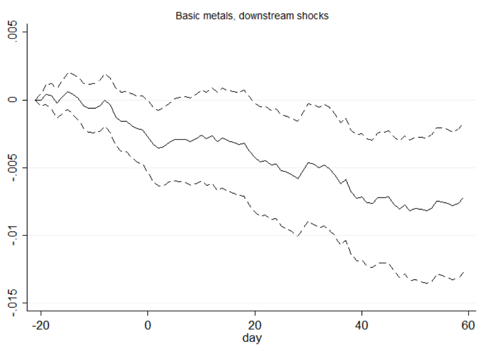
(a) Automobiles and parts



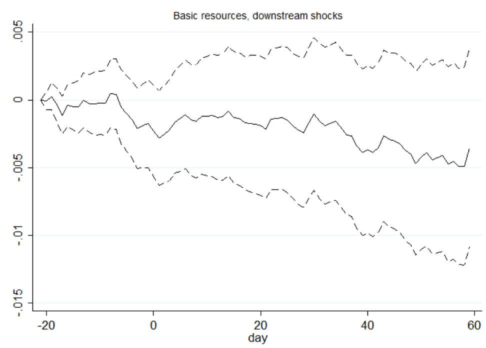
(b) Banks



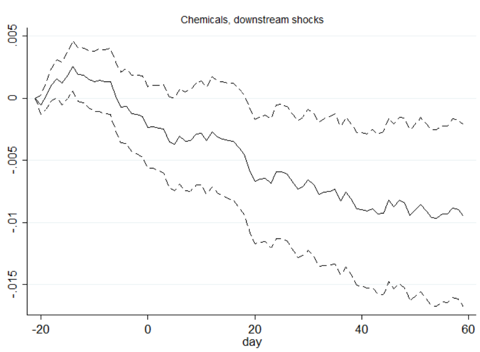
(c) Basic materials



(d) Basic resources



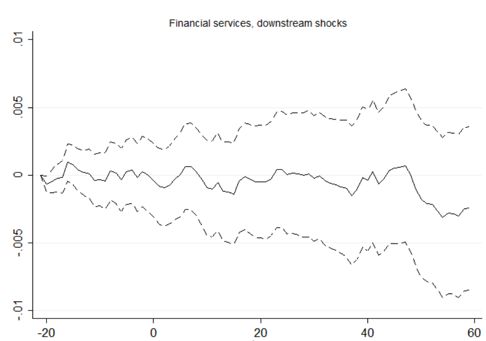
(e) Chemicals



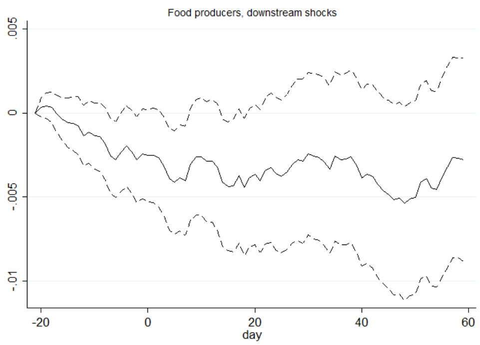
(f) Construction and materials

(g) Food and beverages

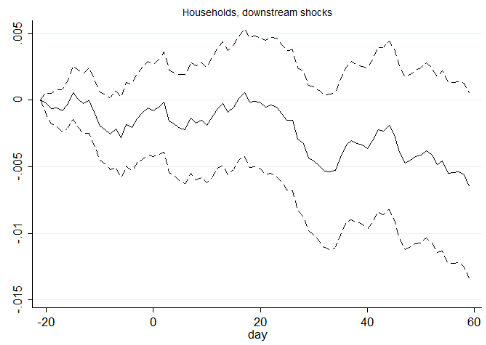
(h) Financial services



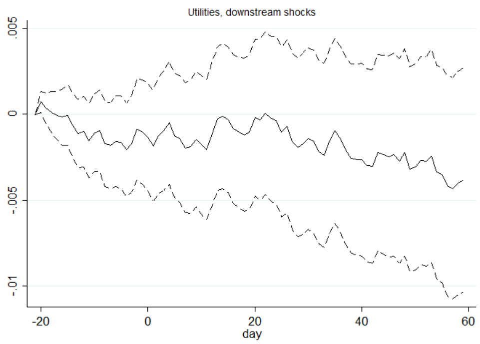
(i) Food producers



(j) Household goods and home construction



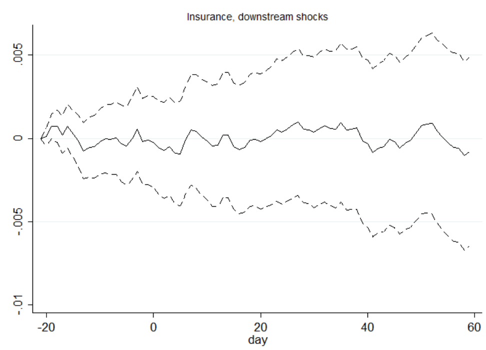
(k) Utilities



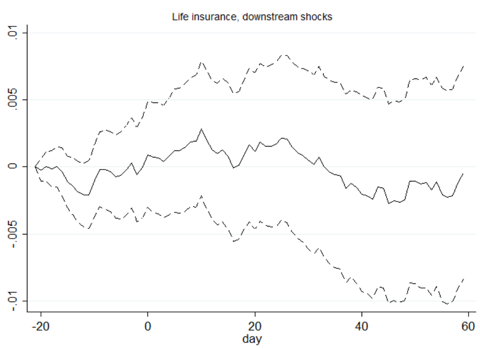
(l) Industrial goods

(m) Industrial producers

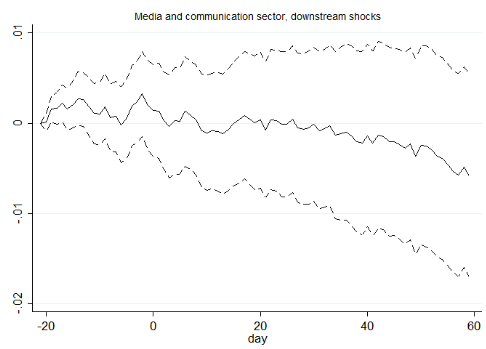
(n) Insurance



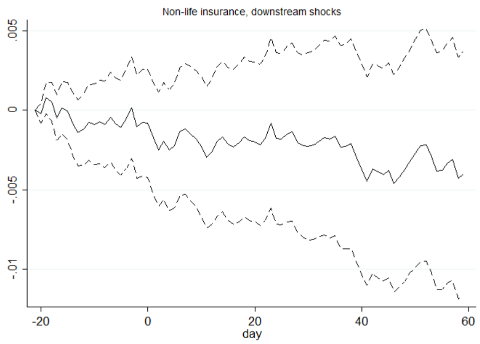
(o) Life insurance



(p) Media and communication

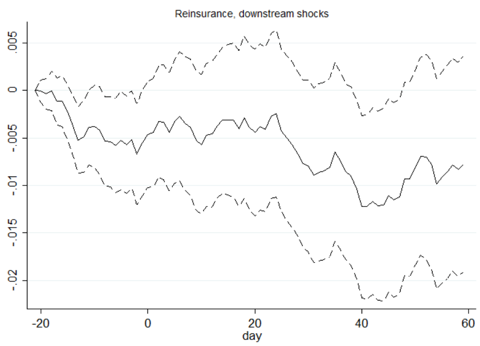


(q) Non-life insurance

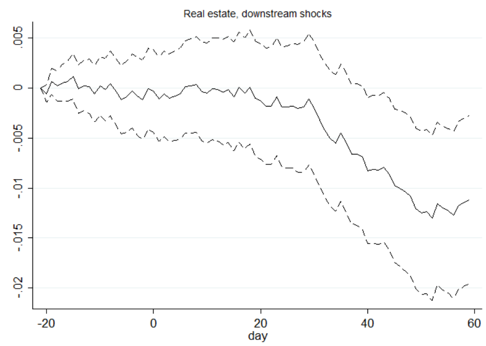


(r) Property and casualty insurance

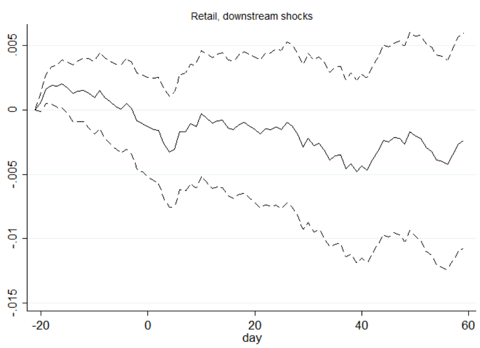
(s) Reinsurance



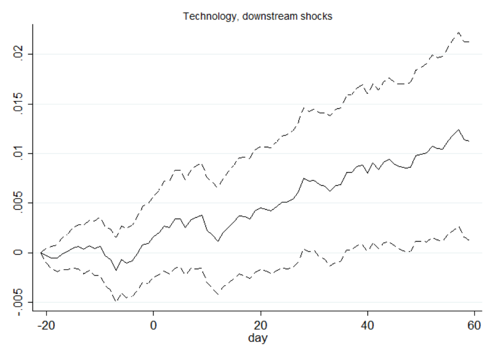
(t) Real estate



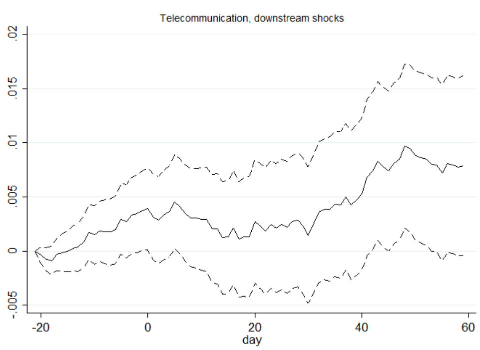
(u) Retail



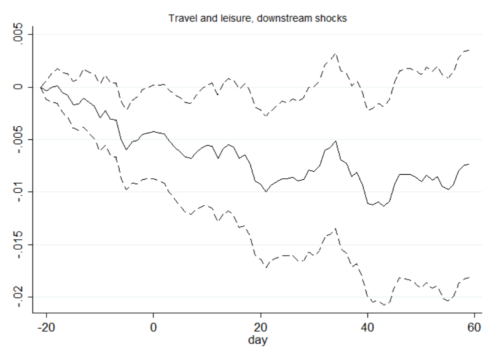
(v) Technology



(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.

References

Acemoglu, D., U. Akcigit, and W. Kerr (2016). Networks and the macroeconomy: An empirical exploration. Nber macroeconomics annual 30(1), 273–335.

Addoum, J. M., D. T. Ng, and A. Ortiz-Bobea (2019). Temperature shocks and industry earnings news. Available at SSRN 3480695.

Anderson, J. E. and E. Van Wincoop (2004). Trade costs. Journal of Economic literature 42(3), 691–751.

Arkolakis, C., A. Costinot, and A. Rodriguez-Clare (2012). New trade models, same old gains? American Economic Review 102(1), 94–130.

Backus, D. K., P. J. Kehoe, and F. E. Kydland (1992). International real business cycles. Journal of political Economy 100(4), 745–775.

Baker, A. C., D. F. Larcker, and C. C. Wang (2022). How much should we trust staggered difference-in-differences estimates? Journal of Financial Economics 144(2), 370–395.

Balboni, C. A. (2019). In harm's way? infrastructure investments and the persistence of coastal cities. Ph. D. thesis, London School of Economics and Political Science.

Baqaee, D. and E. Farhi (2019). Networks, barriers, and trade. Technical report, National Bureau of Economic Research.

Barrot, J.-N. and J. Sauvagnat (2016). Input specificity and the propagation of idiosyncratic shocks in production networks. The Quarterly Journal of Economics 131(3), 1543–1592.

BlackRock (2019). Getting physical. scenario analysis for assessing climate-related risks. BlackRock Investment Institute.

Boehm, C. E., A. Flaaen, and N. Pandalai-Nayar (2019). Input linkages and the transmission of shocks: Firm-level evidence from the 2011 tōhoku earthquake. Review of Economics and Statistics 101(1), 60–75.

Botzen, W. W., O. Deschenes, and M. Sanders (2019). The economic impacts of natural disasters: A review of models and empirical studies. Review of Environmental Economics and Policy 13(2), 167–188.

Burke, M., S. M. Hsiang, and E. Miguel (2015). Global non-linear effect of temperature on economic production. Nature 527(7577), 235–239.

Cadestin, C., K. De Backer, I. Desnoyers-James, S. Miroudot, M. Ye, and D. Rigo (2018). Multinational enterprises and global value chains: New insights on the trade-investment nexus. OECD Science, Technology and Industry Working Papers 2018(5), 0_1–36.

Caliendo, L. and F. Parro (2015). Estimates of the trade and welfare effects of nafta. The Review of Economic Studies 82(1), 1–44.

Caliendo, L., F. Parro, E. Rossi-Hansberg, and P.-D. Sarte (2017). The impact of regional and sectoral productivity changes on the us economy. The Review of economic studies 85(4), 2042–2096.

Carvalho, V. M., M. Nirei, Y. Saito, and A. Tahbaz-Salehi (2016). Supply chain disruptions: Evidence from the great east japan earthquake. Columbia Business School Research Paper (17-5).

Cengiz, D., A. Dube, A. Lindner, and B. Zipperer (2019). The effect of minimum wages on low-wage jobs. The Quarterly Journal of Economics 134(3), 1405–1454.

Choi, J. and Y. Shim (2021). Technology adoption and late industrialization. Technical report, April 2022. Mimeo, Michigan and Chicago.

Conte, B. (2022). Climate change and migration: the case of africa.

Conte, B., K. Desmet, D. K. Nagy, and E. Rossi-Hansberg (2020). Local sectoral specialization in a warming world. Technical report, National Bureau of Economic Research.

Cruz, J.-L., E. Rossi-Hansberg, et al. (2020). The economic geography of global warming. Unpublished working paper, Princeton University.

De Souza, G. and H. Li (2020). The employment consequences of anti-dumping tariffs: Lessons from brazil. University of Chicago working paper.

Dell, M., B. F. Jones, and B. A. Olken (2012). Temperature shocks and economic growth: Evidence from the last half century. American Economic Journal: Macroeconomics 4(3), 66–95.

Dhyne, E., A. K. Kikkawa, M. Mogstad, and F. Tintelnot (2021). Trade and domestic production networks. The Review of Economic Studies 88(2), 643–668.

Di Giovanni, J., A. A. Levchenko, and I. Mejean (2018). The micro origins of international business-cycle comovement. American Economic Review 108(1), 82–108.

Diffenbaugh, N. S. and M. Burke (2019). Global warming has increased global economic inequality. Proceedings of the National Academy of Sciences 116(20), 9808–9813.

Dingel, J. I., K. C. Meng, and S. M. Hsiang (2019). Spatial correlation, trade, and inequality: Evidence from the global climate. Technical report, National Bureau of Economic Research.

Gu, G. W. and G. Hale (2022). Climate risks and fdi. Technical report, National Bureau of Economic Research.

Hong, H., F. W. Li, and J. Xu (2019). Climate risks and market efficiency. Journal of econometrics 208(1), 265–281.

Hsiang, S. M. (2010). Temperatures and cyclones strongly associated with economic production in the caribbean and central america. Proceedings of the National Academy of sciences 107(35), 15367–15372.

International Monetary Fund (2020). Global financial stability report: Markets in the time of covid-19. Washington: International Monetary Fund.

Johnson, R. C. and G. Noguera (2017). A portrait of trade in value-added over four decades. Review of Economics and Statistics 99(5), 896–911.

Jones, C. I. and P. J. Klenow (2016). Beyond gdp? welfare across countries and time. American Economic Review 106(9), 2426–57.

Kahn, M. E., K. Mohaddes, R. N. Ng, M. H. Pesaran, M. Raissi, and J.-C. Yang (2019). Long-term macroeconomic effects of climate change: A cross-country analysis. Technical report, National Bureau of Economic Research.

Kleinman, B., E. Liu, and S. J. Redding (2021). Dynamic spatial general equilibrium. Technical report, National Bureau of Economic Research.

Li, H. (2021). Multinational production and global shock propagation during the great recession. Technical report, Working Paper, University of Chicago February.

Lintner, J. (1965). Security prices, risk, and maximal gains from diversification. The journal of finance 20(4), 587–615.

Lucas, R. E. (1987). Models of business cycles, Volume 26. Basil Blackwell Oxford.

MacKinlay, A. C. (1997). Event studies in economics and finance. Journal of economic literature 35(1), 13–39.

Mondragon, J. A. and J. Wieland (2022). Housing demand and remote work. Technical report, National Bureau of Economic Research.

Panigrahi, P. (2021). Endogenous spatial production networks: Quantitative implications for trade and productivity. Available at SSRN 3982029.

Paris Agreement (2015). Paris agreement. In Report of the Conference of the Parties to the United Nations Framework Convention on Climate Change (21st Session, 2015: Paris). Retrived December, Volume 4, pp. 2017. HeinOnline.

Rosvold, E. L. and H. Buhaug (2020). Geocoded disasters (gdis) dataset. NASA Socioeconomic Data and Applications Center (SEDAC)[data set] 10.

Sharpe, W. F. (1964). Capital asset prices: A theory of market equilibrium under conditions of risk. The journal of finance 19(3), 425–442.

Sirimanne, S. N., J. Hoffman, W. Juan, R. Asariotis, M. Assaf, G. Ayala, H. Benamara, D. Chantrel, J. Hoffmann, A. Premti, et al. (2019). Review of maritime transport 2019. In United Nations conference on trade and development, Geneva, Switzerland.

Somanathan, E., R. Somanathan, A. Sudarshan, M. Tewari, et al. (2015). The impact of temperature on productivity and labor supply: Evidence from indian manufacturing. Indian Statistical Institute: New Delhi, India, 212–231.

Stavins, R., J. Zou, T. Brewer, M. Conte Grand, M. den Elzen, M. Finus, J. Gupta, N. Höhne, M.-K. Lee, A. Michaelowa, et al. (2014). International cooperation: agreements and instruments. Climate change 7(5), 1001–1082.

Timmer, M. P., E. Dietzenbacher, B. Los, R. Stehrer, and G. J. De Vries (2015). An illustrated user guide to the world input–output database: the case of global automotive production. Review of International Economics 23(3), 575–605.

Treynor, J. L. (1961). Market value, time, and risk. Time, and Risk (August 8, 1961).

Wache, B. (2021). Information frictions, global capital markets, and the telegraph.

Woetzel, J., D. Pinner, H. Samandari, H. Engel, M. Krishnan, B. Boland, and C. Powis (2020). Climate risk and response: Physical hazards and socioeconomic impacts. McKinsey Global Institute 22.

Woltjer, P., R. Gouma, and M. P. Timmer (2021). Long-run world input-output database: Version 1.0 sources and methods.