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

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 strike 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. As a result, climate adaptation efforts in one country can have a positive impact on macro-financial performance and stability in other countries through international trade.

JEL-Codes: F420, G140, Q540.

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 their own best interests, may not be motivated to undertake costly climate change mitigation initiatives. This view raises questions about the sustainability of international cooperation in combating climate change.

In this paper, we argue that such a gloomy view is only 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

[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).

a matching-and-stacking difference-in-differences strategy. We match each country that 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 group.

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 restructure supply chains: the affected country sells a smaller share of its output to the downstream country, but spends a greater share of its expenditures on the upstream country. Using a new formula, we decompose the total effect of climate disasters on main upstream and downstream GDP into a term describing the demand/supply shock (fixing the trade shares) and another term describing the trade disruptions. We find that export disruptions weakly decrease downstream GDP, while a greater reliance on imports significantly reduces 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 fall by 1% in the main downstream country and by 1.5% in the main upstream country. 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. In the case of climate disasters that affect ports, the difference is even more pronounced.

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 risks 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 has a lesser impact on international trade, such as airports, does not affect the consequences in main trading partners. Third, we show that foreign climate disasters affect short-run stock market returns only in tradable sectors. There is a greater impact on tradable sectors when climate disasters hit ports. Fourth, foreign long-time climate risks only affect long-run stock market valuations in tradable sectors. 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.[3] 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.[4] 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

[3]See, for example, Sobel (2021).

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

sectors may encounter during the transition to a greener economy).

We contribute to the literature on the economic consequences of climate change.[5] 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, Castro-Vincenzi 2023). Other works have found that extreme climate conditions undermine stock market earnings, returns, and prices (Stroebel and Wurgler 2021, Faccini et al. 2022). 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 largely focused on the effects of climate disasters and climate risks on local areas or countries, while we examine the responses of the country's major trading partners. Second, we demonstrate that international trade is an important propagation mechanism. Specifically, we highlight that only climate disasters that affect port infrastructure can disrupt trade and affect foreign output, and that only tradable sectors are affected in the foreign country. Third, we present empirical evidence that shows that climate disasters are associated with both short-run changes in foreign output and stock returns as well as long-run declines in foreign stock market valuations.

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, Autor et al. 2013, Di Giovanni et al. 2018, Adao et al. 2019) 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 an 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. Like traditional productivity and demand shocks, climate shocks can also affect trade and thus propagate internationally. Surveillance of foreign supply and demand shocks has been critical for a country's external sector stability.[6] We suggest that global governments

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

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

and central banks should also monitor foreign climate shocks and respond accordingly. Different from the propagation of economic shocks, we show that climate shocks can lead to disruptions in trade (particularly those affecting port infrastructure), 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, Feyrer 2021, Gu and Hale 2022, Forslid and Sanctuary 2022), whereas others have studied the impact of climate disasters on domestic suppliers, customers, and labor migration (Barrot and Sauvagnat 2016, Balboni 2019, Gröschl et al. 2023). Other works build quantitative spatial models to study the macroeconomic consequences of climate change (Cruz et al. 2020, Conte et al. 2020, Conte 2022).[7]

We contribute to this literature in two ways. First, past empirical works have focused on the microeconomic impact of climate disasters on individuals and households through microeconomic supply chains, 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, cross-border effects have been assumed by the model to exist in order to compute the spatial and macroeconomic effects of climate change. 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.

[7] 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, industrial production manufacturing 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.[8]

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. Finally, we collect country-month level CPI data also from the IFS.

International Trade and Gross Output We acquire country-bilateral and monthly international trade information from Direction of Trade Statistics (DOTS).[9] 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-

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

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

month level GDP with the corresponding GDP to gross output ratio.

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, $X_{i,t}$:[10]

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

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:[11]

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

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

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

[10] 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: $X_{i,t} = Y_{i,t}+IM_{i,t}-EX_{i,t}$.

[11] 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 employment 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. Additionally, we obtain data on the three-month yield on government bonds.

Climate Disaster Data and Disaster Locations We acquire information about global climate disasters from the Emergency Events Database (EM-DAT).[12] We learn, for each disaster, the start and end date, monetary value of damage, affected persons, and total deaths.[13] 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.[14]

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

[12] 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. Guha-Sapir and Below (2002), Franzke (2021), among others, have compared EM-DAT to other datasets about climate disasters and found that this dataset has high quality. Table A.2 presents the summary statistics of climate disasters by types. In our sample, floods are the most common form of climate disasters, followed by storms. Among the types of natural disasters that cause the most damage, landslides and storms account for the largest fraction of the affected country's GDP.

[13] 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.

[14] Appendix Figure A.3 shows the geographical distribution of the climate disasters and ports.

may be exposed to the physical impacts of future climate disasters.[15] Since climate change risks generally refer to a long-term view, we fix a country's climate risk to its value in 2018.[16]

3 Empirical Strategy for the Macroeconomic Effects of Climate Disasters

To study the macroeconomic effects of a climate disaster on the affected country and the foreign economies that trade intensively with the affected country, 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 with a most similar, no-disaster counterpart, which constitutes 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 event window.

We ensure that no other climate disasters happen in the pre-period of each disaster. That is, we focus only on the disasters whose windows do not overlap. If more than one disaster 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.

[15]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 change hazard index is therefore associated with higher climate risks.

[16]The Verisk Maplecroft data is only available from 2013 to 2018. 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.

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 and is the most similar to country i according to propensity score matching.[17] The treatment and control groups for each disaster d are then stacked into a new data set.[18] The regression specification is the following:

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

where $y_{i,d,t}$ denotes the outcome variable of country i in month t due to climate disaster d. $\mathbb{I}_t \left\{ m \text{ Months After Climate Disaster } d \right\}$ 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 $\bar{t} = 4$.[19] 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.[20]

We investigate the average impact of a disaster over time (in an average month of the

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

[18] 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.

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

[20] 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.

first four months after a disaster occurs) using the following cross-sectional specification:

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

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

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:

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

$\frac{Damage_{i,d} \times \pi_{i,j,t}}{GDP_{j,\bar{y}}}$ 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. 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. As a result, countries may be able to reduce the harms caused by climate disasters on their consumption by increasing international borrowing through which they can share the risks with other nations.[21] 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.

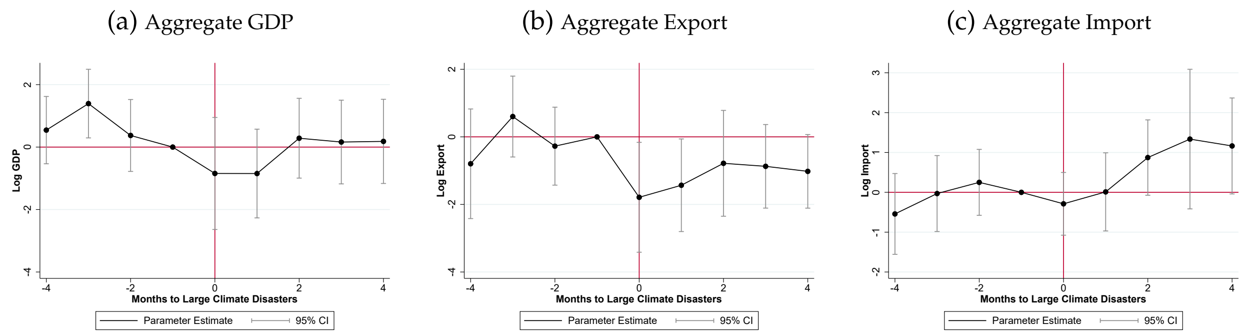
Figure A.4 shows that a climate disaster increases the affected country's consumer price index from month 0 to month 2 after the disaster starts.

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 to international trade – ports – lead to more disruptions in both international trade and foreign production. The climate disasters that do not hit ports do not have such effects. The critical role

[21] This finding is consistent with Yang (2008), who shows that climate disasters increase the affected country's international borrowing and imports.

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



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.

of ports in international trade is proven by the fact that 80% of global trade is conducted through ports (Sirimanne et al., 2019).

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 relies 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. As a result, the loss of income effect dominates, resulting in a decline in imports.[22]

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, or imports from the main upstream. Additionally, the disaster that does not hit a port significantly increases total imports. 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

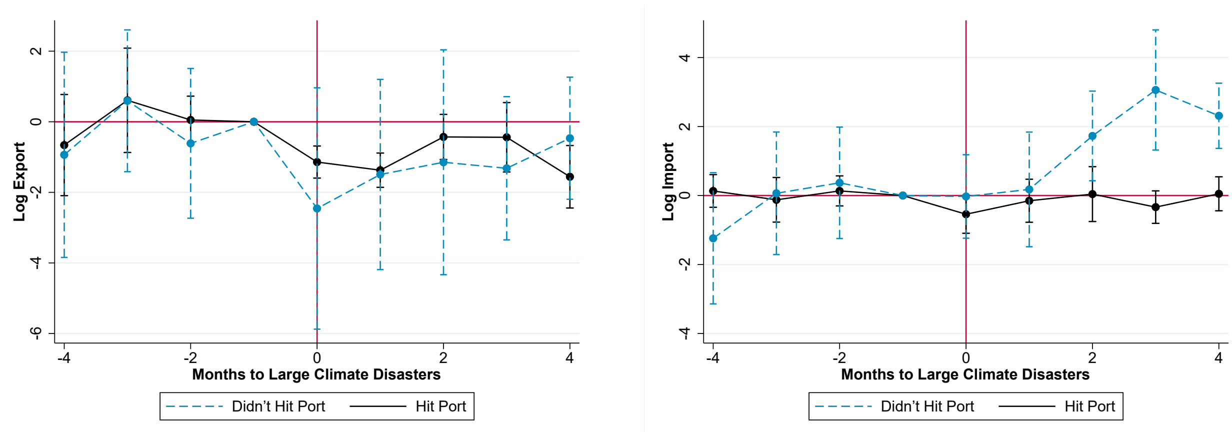
In this section, we show that the climate disasters that affect international trade infrastructures can significant undermine economic performance in upstream and downstream countries. This indicates that a country can be negatively impacted by not only their own climate disasters, but also those that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

[22] In Appendix Figure A.5 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.

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, if it hits a port, decreases the downstream country's GDP by 0.51% and the upstream country's GDP by 0.36% in the first month (see Table 5).

Table 4 also 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.6 shows that a climate disaster only weakly decreases both the total imports by the downstream country and the 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 substi-

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. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

tute their suppliers and customers to offset the decline in bilateral trade. Likely due to such substitution, as shown in Appendix Figure A.7, 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.5 shows that emerging market and developing economies are more vulnerable to 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

Table 3: **Impacts of Climate Disasters in the Affected 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. In order to interpret the coefficients, we multiply them by the mean of the damage ratio in each sample. *** p<0.01, ** p<0.05, * p<0.1.

downstream or upstream country if the downstream or upstream country is an emerging market/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 the upstream or downstream country is exposed, the cross-border spillover effect is not significantly affected by whether the disaster-hit country is an emerging market or developing economy.

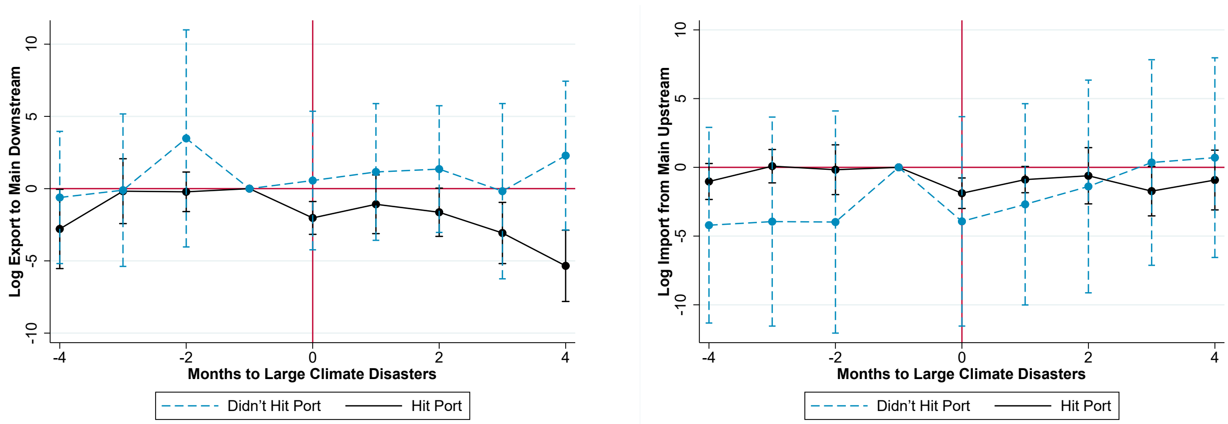
Table 4: **Impact of Foreign Climate Disasters on Production**

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**

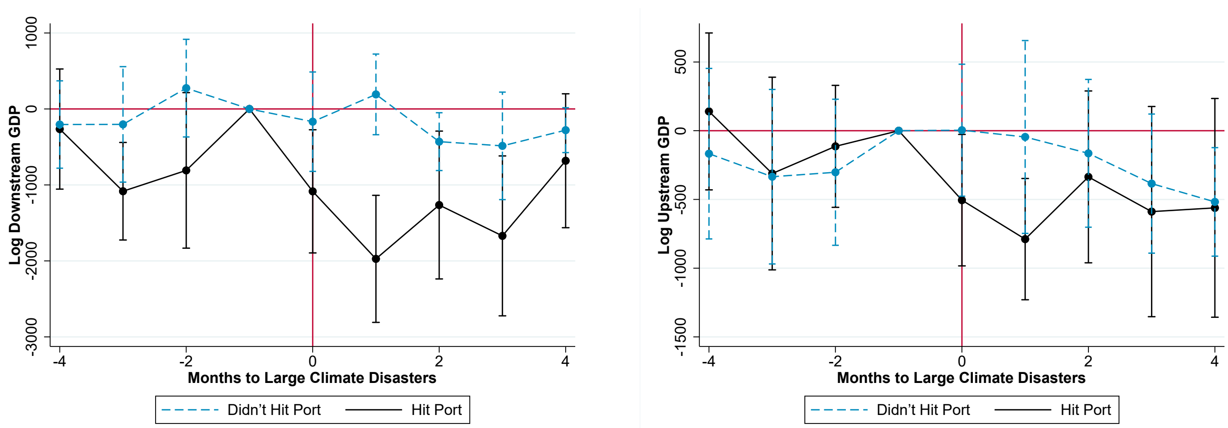
(a) Export to Main Downstream (b) Import from Main Upstream



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 the degree to which the affected country's exports and imports are disrupted relative to its total output and total expenditure.[23] Trade disruptions

[23]International trade networks are restructured when parts of them are affected by shocks. Countries source more products from and sell more goods to parts of the world that are not affected. As a result, a

Table 5: **Impacts of Climate Disasters 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.

occur when exports decrease relative to total output - export share decreases - or when imports decrease relative to total expenditures - import share decreases. Otherwise, exports and imports are considered strengthened.

Figure 5a shows that a climate disaster only weakly decreases the affected country's export share, whether the disaster hits a port (regression result of Equation 1 using the disaster country's export share as the dependent variable). 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 disrupt exports.

However, Figure 5b shows that, due to climate disasters, countries become more reliant on foreign supplies (regression result of Equation 1 using the disaster country's import share as the dependent variable). 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. This suggests that countries engage in international risk sharing: by increasing international borrowing, they can import more and reduce the negative effects of climate disasters on current output and consumption. A weakly lower export share and a higher import share also suggest that climate disasters increase countries' trade deficits and worsen their external balance.

Figure 6 shows that climate disasters that hit ports significantly decrease the affected country's output share to the main downstream country (regression result of Equation 1 using $S_{k,i,t}$ as the dependent variable) and significantly increase the country's expenditure share on the main upstream country (regression result of Equation 1 using $\pi_{i,j,t}$ as the dependent variable). 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

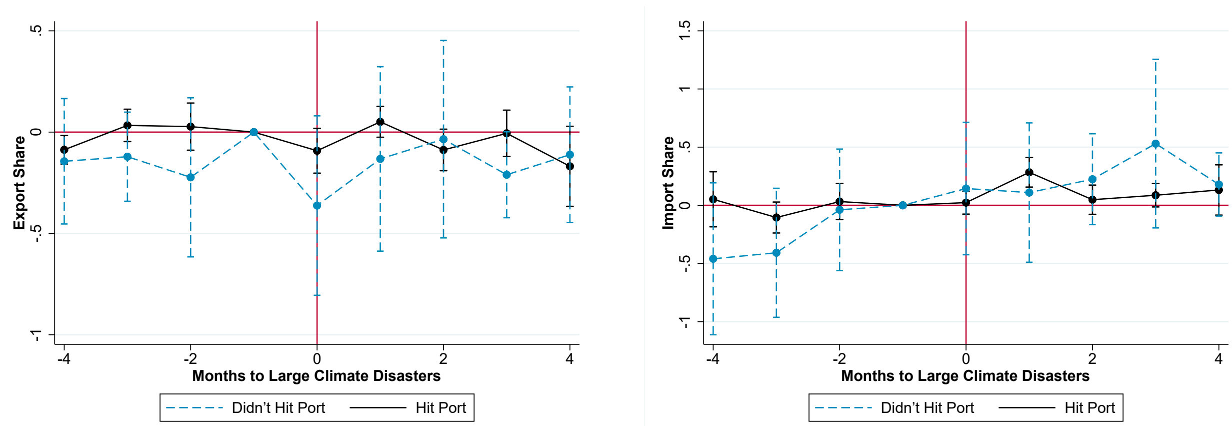
country's market share in other countries is affected, resulting in trade disruptions. This is a prominent feature of international trade network that distinguishes it from sectoral input-output production chains, which are generally considered to be fixed by the technology of production.

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.

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

(a) Export Share (b) Import Share



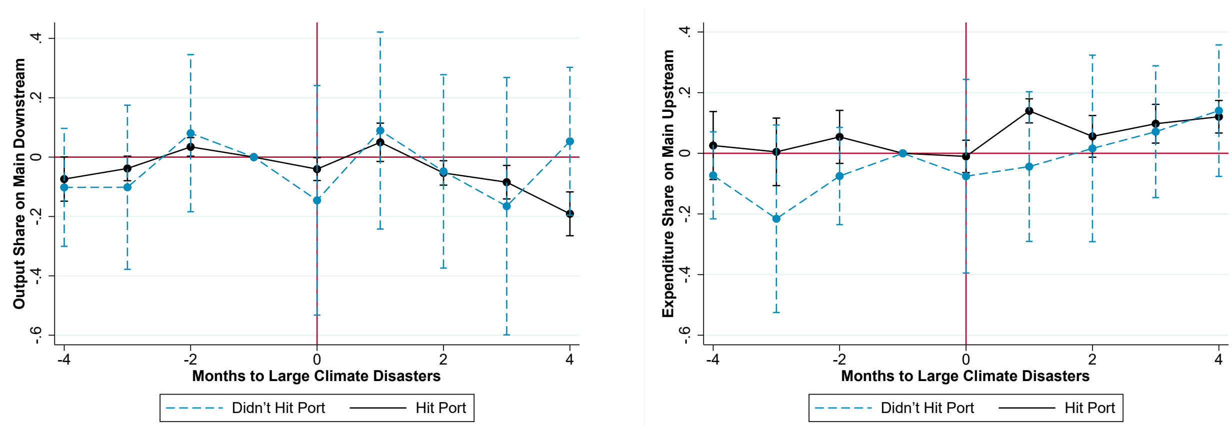
Description: This figure contains the coefficients of the effect of a climate disaster on the log export and import of the country it directly hit using the stacked event-study model 1. The x-axis contains the number of months to the disaster's starting date. Export share is midstream country's aggregate 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.

4.5 Impact of Trade Disruption on Cross-border Spillovers

We investigate how the impact of a climate disaster on a foreign country depends on the trade disruption that it causes. A climate disaster (if it hits a port) reduces the affected country's supply of intermediate input and final goods to downstream countries and reduces the country's demand of these goods from upstream countries. Meanwhile, as we show in Section 4.4, climate disasters can disrupt trade and restructure international supply chains. If the trade disruption makes upstream and downstream countries less open to trade, 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

Figure 6: **Impact of Climate Disasters on Midstream Output and Expenditure Share Traded with the Main Downstream and Main Upstream Country**

(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.

Table 6: **Disaster Effect on Midstream's Output and Expenditure Share Traded with the Main Downstream and Main Upstream Country**

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Output Share	Expenditure Share	Output Share	Expenditure Share	Output Share	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.

shocks (fixing the trade shares) and (2) trade disruptions – contribute to the consequences of climate disasters in upstream and downstream economic performances.

We propose a new decomposition formula that accounts for the contributions of both 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:

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

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.[24] If disasters did not disrupt trade at all, the midstream country i's exports would decrease by the disaster's damage divided among all downstream countries, according to the midstream country's fixed output shares. To determine downstream exposure, the loss is divided by downstream GDP in the previous year.

Trade disruption refers to the decline in midstream exports as a percentage of midstream total output. The term will be equal to zero if climate disasters only result in supply shocks to downstream countries and do not disrupt trade at all. The downstream country's expenditure share on the midstream accounts for 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:

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

where, on the right hand side, both the supply shock and trade disruption are interacted with a dummy that indicates whether month t is after the start date of disaster d. As a measure of the disruption to trade caused by a disaster, we use the estimated effect on the midstream country's output share sold to the downstream as predicted by Equation 2. We have reported the effect in Table 6 and we denote the predicted output share with $\widehat{d(S_{k,i,d})}$.[25] The definition of other variables in this regression is the same as those in

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

[25] We study the impact of climate disasters on midstream country's sales share to the main downstream country with the midstream regression specification Equation 2. The regressor is the damage ratio in the midstream country – the disaster's damage relative to the midstream country's GDP. Hence, the predicted output share, $\widehat{d(S_{k,i,d})}$, is not co-linear with the exposure measure (the supply shock) in the main downstream country.

Equations 4 and 7.[26] Since the climate disasters that do not hit ports cause no significant disruptions in trade, we focus on the sample of 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 i's expenditure share spent over j as predicted by Equation 2. We have reported the effect in Table 6.[27]

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

The trade restructuring channel contributes negatively to GDP in downstream countries, but contributes positively to GDP in upstream countries. Table B.1 shows that openness to trade increases GDP in both upstream and downstream countries.[28] 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, downstream countries suffer from a disruption of trade, which exacerbates the negative consequences of climate disasters. Conversely, for upstream countries, trade is strengthened, which reduces the negative impact of climate disasters. Trade restructuring is estimated to have a small effect on downstream GDP, but a much larger

[26] We show how we derive this formula in Appendix Section B. We define a channel's contribution, for example, that of a supply shock to downstream GDP, as follows: $\frac{\text{Cov}(\text{Supply Shock}_{j,d}, \text{Supply Shock}_{j,d} + \text{Trade Openness}_{j,d})}{\text{Var}(\text{Supply Shock}_{j,d} + \text{Trade Openness}_{j,d})}$. Supply $\text{Shock}_{j,d}$ and Trade $\text{Openness}_{j,d}$ are defined in Equation 8. To construct these variables, we use the estimated coefficients. A similar estimation and decomposition method is used in Klenow and Rodriguez-Clare (1997), Alviarez et al. (2020), Mondragon and Wieland (2022), among others.

[27] We study the impact of climate disasters on midstream country's expenditure share on the main downstream country with the midstream regression specification Equation 2. The regressor is the damage ratio in the midstream country – the disaster's damage relative to the midstream country's GDP. Hence, the predicted expenditure share, $\widehat{d(\pi_{i,j,d})}$, is not co-linear with the exposure measure (the demand shock) in the main upstream country.

[28] 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).

effect on upstream GDP based on the coefficients.[29]

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. On the other hand, the demand shock channel contributes 146.6% and the supply chain reorganization channel contributes -46.6%. According to the second result, although a disaster reduces a country's total income and expenditure, it forces it to spend a greater share on foreign suppliers, which is beneficial to these countries. Approximately one-third of the loss caused by the demand shock is offset by strengthened trade linkages. Such asymmetric trade disruption effects in upstream and downstream countries again confirm that international trade is an important propagation mechanism.

4.6 Robustness and Other Findings

Impact of an Average Climate Disaster We 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.8 and A.9 show 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.[30]

Interacting Disaster Exposures with Port Dummy Appendix Table A.3 and Appendix Table A.4 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.

[29] 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%.

[30] Botzen et al. (2019) argue that, while the EM-DAT is the most widely used database on climate disasters, its measures of monetary losses could be subject to measurement errors. We show that our results are robust if we measure climate disasters using a dummy rather than the recorded monetary damages.

Different Measures of GDP We use GDP per capita, detrended GDP, and seasonal adjusted GDP as alternative measures for production.[31] Appendix Figure A.10 and A.11 suggest that our findings in the main analysis are robust across these different measures.

Different Measures of Damage Exposure We also use demeaned and detrended damage exposure measures to estimate the climate disaster effect.[32] Appendix Figure A.12 shows that the climate disaster effect estimated from different measures is consistent with our main findings.

Other Transport Infrastructure: Airport We control for disaster damage in the regressions, but readers may still be concerned that the disasters that hit ports may occur in more prosperous areas, which may contribute to the more adverse effects of climate disasters. To rule out this confounding channel, in Appendix Figure A.13, we show that while the climate disasters that hit airports reduce domestic GDP more than those that do not hit airports, 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) the foreign countries that are both main upstream and main downstream. Appendix Figure A.14 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. Figure A.15 shows that disaster-hit countries' exports to main downstream countries decline, regardless of whether the downstream countries are also main upstream nations. In addition, disaster-hit countries' imports from main upstream countries decline, regardless of whether the upstream countries are also main downstream nations.

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

[32] We demean the damage measure by running a regression with a disaster level fixed effect and calculating the residuals. We use a linear regression to estimate the trend in damage measure against time and then remove it from the estimated trend.

Geographical Propagation We study how climate disasters propagate according to geographical and cultural distances. 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.6, we find weak evidence that the countries that are closer, contiguous, share the same language or legal system with the affected country are more affected by the disaster. However, given that the estimates are small in magnitude and lack statistical power, this suggests that how close countries are in distance or in culture 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.

Whether Disasters Hit Populous Regions Climate disasters are more likely to be severe in densely populated areas. We calculate the affected population ratio by dividing each disaster's directly affected population by the country's population. Following this, we divide the climate disasters into two sub-samples based on the median ratio of the affected population. According to the Appendix Table A.7, disasters that have an above median affected population ratio cause a greater loss of production in midstream, upstream, and downstream countries.

Excluding Neighboring Countries In Appendix Table A.8, we exclude from the sample the main upstream and downstream countries that are contiguous to the countries that are affected by climate disasters. We find that our results remain robust. This observation is also consistent with the findings in Appendix Table A.6 which finds contiguity only weakly explains the cross-border propagation effect.

Impact of Exposures to Foreign Climate Disasters through Both Importing and Exporting We investigate whether including the exposures to foreign climate disasters through both importing and exporting will change our findings. In the analysis we have conducted, the downstream exposure measure is based on how much the disaster-hit country exports to downstream countries, and the upstream exposure measure is based on how much the disaster-hit country imports from upstream countries.[33] Table A.9 shows that the exposure to foreign climate disasters through importing (the upstream exposure measure) does not negatively impact production in downstream countries, and the exposure to foreign climate disasters through exporting (the downstream exposure measure) does

[33]This approach is also taken in Barrot and Sauvagnat (2016), Carvalho et al. (2016), Boehm et al. (2019), among others.

not negatively impact production in upstream countries.[34] This finding is driven by the fact that we document in Figure A.16: for the countries that are only main upstream or only main downstream, there is negative or no correlation between the midstream country's expenditure share and its output share with these countries.[35]

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.17, 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.[36]

A Model that Studies the Impact of Openness to Trade and International Risk Sharing on Country Risk Exposures In Section C, we build a model that shows how foreign shocks affect the domestic economy through openness to trade and international risk sharing.[37] To generate analytical solutions and demonstrate insights, we examine three scenarios: (1) trade autarky with no international risk sharing;[38] (2) frictionless trade with no international risk sharing; and (3) frictionless trade with perfect international risk sharing.[39] With the model, we show that openness to trade expose countries to foreign risks. Thus, by assisting foreign countries to develop climate resilience, which reduces the magnitude and volatility of foreign climate shocks, domestic welfare can be improved because in the domestic economy, the average consumption increases and consumption volatility decreases. When countries are symmetrical (having the same mean and volatility of country-specific shocks), openness to trade can increase domestic consumption's mean and decrease its volatility, increasing certainty-equivalent welfare. On top of openness to

[34] We consider the following specification: $y_{j,d,t} = \beta_1 \times Post_{d,t} \times \frac{Damage_{i,d} \times S_{j,i,t}}{GDP_{j,\bar{y}}} + \beta_2 \times Post_{d,t} \times \frac{Damage_{i,d} \times \pi_{i,j,t}}{GDP_{j,\bar{y}}} + \alpha_{j,d} + \lambda_{t,d} + \epsilon_{j,d,t}$, where $y_{j,d,t}$ denotes the GDP in main upstream or main downstream country.

[35] In the case of countries that are both main upstream and main downstream, the correlation between the midstream country's expenditure share and its output share with these countries is only about 0.5.

[36] In an average month during the event window, climate disasters that affect ports reduce consumption by 0.46% in the directly affected country, 0.36% in the main downstream country, and 0.35% in the main upstream country based on the estimated coefficients and average damage ratios/exposure measures.

[37] The model builds on Caselli et al. (2020): we introduce the risk sharing mechanism and investigate how it affect mean and volatility of a country's consumption.

[38] As a result of trade autarky, since countries neither export nor import, due to the Balance of Payments, they are unable to trade international assets or share international risks.

[39] According to the literature, international risk sharing refers to the cross-border trade of financial assets (Cochrane 1991, Backus et al. 1992, Townsend 1994, Yang 2008). When countries suffer from bad shocks, they borrow from other countries and run a trade deficit. In the event of a goods shock, a country may run a trade surplus by lending to other countries. By doing so, they will be able to smooth consumption over time and reduce the volatility of consumption.

trade, international risk sharing further exposes domestic consumption to foreign shocks. When countries are symmetrical, international risk sharing can further increase domestic consumption's mean and decrease its volatility (if the number of countries and the trade elasticity is large enough), thus increasing certainty-equivalent welfare.[40]

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

Using a financial market event study approach, we examine how climate disasters affect stock market returns in the main trading partners.[41] As stock market data is available at the country-sector level, we can understand how climate disasters impact sectoral economic performances of major trading partners. We can also investigate such impacts on a more frequent basis.

5.1 Financial Market Event Study Analysis

Different from the study on the real economy, the financial market event study uses the counterfactual returns (the "normal returns") predicted by the Capital Asset Pricing Model (CAPM, Treynor 1961, Sharpe 1964, Lintner 1965) as the control group, whose coefficients are calculated based on how the asset's returns compared to the aggregate market returns in the pre-period. During the event window, the difference between the actual returns and the normal returns is referred to as the "abnormal returns". These abnormal returns are indicative of the daily impact of the climate disaster on the stock market. By aggregating the daily abnormal returns over the duration of the event window, the cumulative abnormal returns can be calculated, which measures the impact of the disaster on the stock market's total returns during the event window.

We use the following specification to study the impact of climate disasters on stock markets in the major downstream countries.[42] Use $RE^{s}_{k,t}$ to denote the return of the stock index in downstream country k, sector s, and on day t.[43] Subtracting the risk free rate (measured with the 3-month government bond yield in country k, $r^{f}_{k,t}$), we get the excess

[40] For international risk sharing to reduce the volatility of consumption (as compared to countries open to trade only), it requires that $(N-1)\theta \geq 2$, where N denotes the number of countries and θ denotes the trade elasticity.

[41] A summary of the financial market event study method can be found at MacKinlay (1997). Faccini et al. (2022), who study climate disaster and policy shocks on firm stock prices, use a similar method.

[42] We examine the same set of main downstream countries as we studied the macroeconomic effects.

[43] The aggregate stock market is denoted with $s =$ TOTMK.

return: $re^s_{k,t} = RE^s_{k,t} - r^f_{k,t}$. According to the CAPM model, the daily stock excess returns at country-sector level and the daily stock excess returns at country aggregate level and world sector aggregate level follow the following pattern:

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

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

We estimate this model for each disaster d that occurs on date t using the estimation window that begins 12 months prior to the disaster start date and ends one month prior to the disaster, which is $[t-12, t-1]$ in months or $[t-240, t-21]$ in trading days.[44] 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 global level return on this sector and the country-level aggregate market return.[45] We consider the same event window as in the analysis on the real economy: $[t-1, t+4]$ 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:

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

$$CAR^s_{k,x} = \sum_{\tau=t-20}^{t+x} AR^s_{k,\tau} \text{ , where } x \in [-20, 80].$$

Same as the analysis on the real economy, we normalize the cumulative abnormal returns on month $t-1$ or day $t-20$ to 0: $CAR^s_{k,-20} \equiv 0$. Hence, $CAR^s_{k,x}$ measures the $(x+20)$-day cumulative abnormal return: total returns in the downstream country's stock market for a period of $(x+20)$ days beginning one month (20 trading days) before the start of the disaster. We estimate the average impact of all climate disasters on downstream countries' sectoral stock indices by calculating the means and confidence intervals for all disasters. If we were to obtain 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 recalculate the calculations for the main upstream countries.

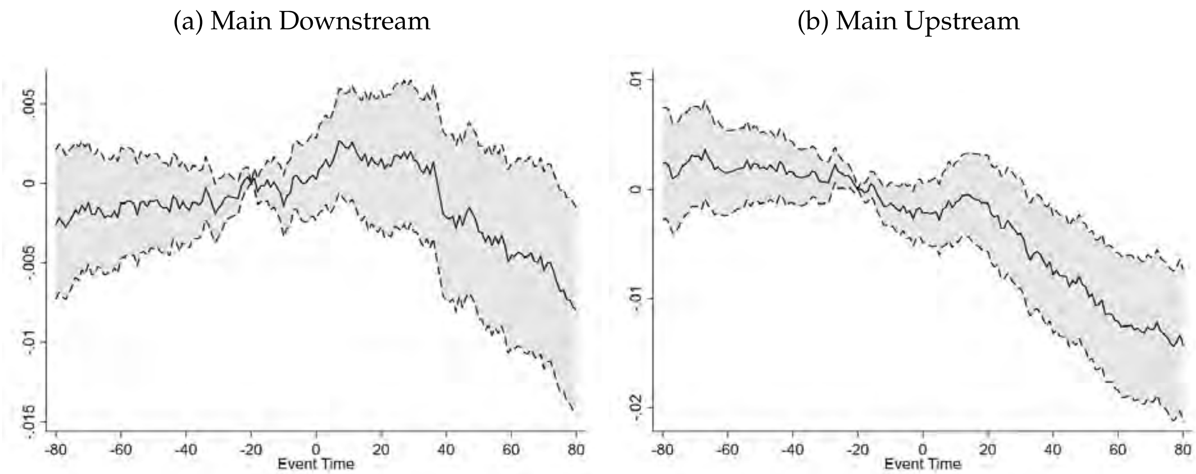
Figures 7 shows that the cumulative abnormal returns in the aggregate stock market is about 1.5% in the main upstream country and about -1% in the main downstream coun-

[44] Our calculation assumes that there are 20 trading days in each month, whereas in reality, there may be 20 or 21 trading days in a month.

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

try. These effects are significant at 95 percent confidence interval in 80 trading days (4 months). 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%) as documented in International Monetary Fund (2020). Additionally, they are comparable to the loss in main downstream and upstream GDP that we documented in Section 4.3. Furthermore, upstream stock markets respond more quickly than downstream stock markets. It is likely that downstream customers can take advantage of inventories to produce before supplies run out.

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



Description: These figures plot cumulative abnormal returns in the stock market indexes in the main downstream and upstream countries from 80 days prior to the disaster to 80 days after it. The shaded area represents 95 % CI.

Only the tradable sectors of downstream and upstream countries exhibit negative and significant losses due to foreign climate disasters. Figure D.3 plots the cumulative abnormal returns in sectoral stock market indices in the main downstream country. Figure D.4 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 automobile sector stocks are as large as -1.8% in the main downstream country and -2% in the main upstream country. Conversely, the bank and financial service, telecommunication, and other nontradable sectors do not respond significantly to foreign climate disasters. Again this highlights that international trade is an important cross-border propagation mechanism for climate disasters.

Other Major Top Trade Partners In Figure D.1, we present the average of the cumulative abnormal returns of the top 3/top 5 downstream countries and the top 3/top 5 upstream countries. Despite the smaller magnitudes, these effects remain robust.

Placebo Tests In Figure D.2, we show that in the disaster-hit country's top 10 to top 20 exporting and importing partners, the aggregate stock market is not significantly affected by the disaster.

5.2 Exposures to Foreign Climate Disasters and Stock Market Returns: Cross-sectional Analysis

In both downstream and upstream countries, we find that greater exposure to climate disasters results in more negative cumulative abnormal returns. Such negative impacts are more profound for the tradable sectors. Further, if climate disasters strike ports, stock market losses in tradable sectors of downstream and upstream countries are more severe.

We first consider the regression specification for downstream countries. On the left-hand side, we use the cumulative abnormal returns in the downstream country k sector s stocks during a period that begins one month (20 trading days) before the start of the disaster and ends 4 months (80 trading days) after the start of the disaster, i.e. $CAR^{s}_{k,80}$ (see Section 5.1). Same as Section 3.2.2, we capture the downstream country's exposure to the midstream climate disaster with $\frac{Damage_{i,d} \times S_{k,i,t}}{GDP_{k,\bar{y}}}$. We first examine this impact on the aggregate market level:

$$CAR^{\text{TOTMK}}_{k,80} = \alpha_1^{TOTMK} \frac{Damage_{i,d} \times S_{k,i,t}}{GDP_{k,\bar{y}}} + \delta_i + \delta_k + \gamma_y + \epsilon^{s}_{d}. \tag{10}$$

This regression is run at 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 time that the disaster hits, t, and the previous year for which we get the downstream GDP, $GDP_{k,\bar{y}}$, and the current output share, $S_{k,i,t}$. The cross-disaster variations identify α_1^{TOTMK}, which govern how exposures to foreign climate disasters affect the aggregate stock market returns in downstream countries. To estimate the impact on the main upstream countries, again we replace the main downstream country k with the main upstream country j and we replace the downstream exposure measure with the upstream counterpart.

Column 1 and Column 4 of Table 7 show that in both downstream and upstream countries, exposures to midstream climate disasters lead to significant declines in stock market returns on the aggregate level. These findings are comparable to what we found for the real economy. Based on a similar calculation to Section 4, we conclude that an average climate disaster reduces the returns in the main downstream and the main upstream stock market by 0.7% and 0.8%, respectively.[46] Other columns in Table 7 show that these findings are robust to alternative fixed effect controls and clustering of standard errors.

Table 7: **Impact of Climate Disasters on Upstream and Downstream Stock Markets**

Dependent Variable: Cumulative Abnormal Return in Stock Market								
	With Fixed Effect						OLS	
	Downstream			Upstream			Downstream	Upstream
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Exposure to Foreign Disaster	-1,421***	-799.6*	-1,006**	-1,152**	-1,407***	-1,432**	-1,028**	-933.2**
	(369.3)	(456.8)	(385.7)	(500.4)	(436.5)	(536.6)	(402.9)	(446.7)
	[420.3]	[506.6]	[467.6]	[504.0]	[485.7]	[504.2]	[429.3]	[451.7]
Observations	381	381	381	381	381	381	396	396
Midstream Cou. FE	Yes	Yes	Yes	Yes	Yes	Yes	No	No
Downstream Cou. FE	No	Yes	Yes	No	No	Yes	No	No
Upstream Cou.FE	No	No	No	No	Yes	No	No	No
Year FE	Yes	No	Yes	Yes	No	Yes	No	No
Mean Dep. Var	-0.00502	-0.00502	-0.00502	-0.0138	-0.0138	-0.0138	-0.00761	-0.0142
R^2	0.0767	0.0745	0.0725	0.0834	0.0830	0.0812	0.0814	0.0852
Effect in 4 Months	-0.711%***	-0.400%*	-0.503%**	-0.804%**	-0.985%***	-1.002%**	-0.514%**	-0.653%**

Description: This table presents the estimated parameters of model 10. The sample is composed of trade partners of countries hit by a large climate disaster. We constrained the sample to observations at 80 trading days after the disaster shock. "Average Effect in 4 Months" presents the damage effect on stock market returns in disaster-hit countries' main trade partners. The effect size is calculated based on the coefficients from model 10 and measured in percentage points, based on the coefficients estimated in columns 3 and 6. Robust standards error in parentheses are two-way clustered at disaster-hit country and stock market country level. Robust standards error in brackets are clustered at disaster-hit country level. *** p<0.01, ** p<0.05, * p<0.1.

Sector Tradability and Cross-border Spillovers of Climate Disasters We show that in the downstream and upstream countries, sectors that are more tradable respond more strongly to midstream climate disasters. Furthermore, such difference is more profound for the climate disasters that hit ports. 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:

$$CAR^s_{k,80} = \mu \frac{Damage_{i,d} \times S_{k,i,t}}{GDP_{k,\bar{y}}} + \lambda \frac{Damage_{i,d} \times S_{k,i,t}}{GDP_{k,\bar{y}}} \times Trade^s_t + \delta_i + \delta_k + \gamma_y + \zeta^s + \epsilon^s_d, \tag{11}$$

where $Trade^s_t$ is a variable that measures how tradable sector s is at time t. In particular, we consider two measures of tradability: (1) TD^s_t, which equals sector s' total trade divided by the sector's total GDP on the world level;[47] (2) a dummy variable TS^s, which equals 1 if the sector belongs to basic material, industrial production, or consumer goods sectors, which are traditionally believed to be the tradable sectors.[48] We control for the downstream country fixed effect, the midstream country fixed effect, the year fixed effect, and the sector fixed effect (which captures the level effect that sector tradability has on the

[46] We multiply the estimated coefficients with the exposure measure of an average disaster that is summarized in Table A.1.

[47] This measure is on the sector-year level. The data source is the World Input-Output Database (Timmer et al., 2015) and the long-run World Input-Output Database (Woltjer et al., 2021).

[48] In our dataset, these tradable sectors include personal goods (PERSG), commodity chemicals (CHEMS), automobiles (AUPRT), basic resources (BRESR), leisure goods (LEISG), food producers (FOODS), household goods and home construction (HHOLD), basic materials (BMATR), food and beverage (FDBEV).

stock returns). To study the effects in upstream countries, we replace downstream country k with the upstream country j, as well as the downstream exposure measure with its upstream counterpart, and estimate the same model.

Table 8 shows that, compared to nontradable sectors, tradable sectors in foreign countries are more adversely affected by foreign climate disasters. Columns 1 to 4 show that the interaction term between the exposure to foreign climate disasters and sector tradability is negative and significant, but that the exposure measure alone does not have a significant effect. This shows that tradable sectors are entirely responsible for the negative impact of climate disasters on foreign stock markets. According to Columns 1 and 3, on average, tradable sectors' stock returns decline by 0.22% more than those of non-tradable sectors in the upstream country and by 0.13% more in the downstream country.[49] Using the estimated coefficients in Columns 2 and 4, we can estimate the impact on each sector. For example, in the upstream country, the returns of the automobile sector decline by 0.24% more than those of the real estate sector, while in the downstream country, they decline by 0.17% more.[50] In Table D.3, we find that climate disasters remain significant impacts on foreign tradable sector stocks, if we cluster the standard errors on a disaster country-stock market country bilateral level or on a disaster country level.

Moreover, we demonstrate that, when disasters strike ports, tradable sectors in foreign countries will suffer a greater loss. As can be seen in Columns 5 to 8 of Table 8, when considering the sample of climate disasters that hit ports, the interaction terms between exposure to foreign climate disasters and sector tradability exhibit larger coefficients. These coefficients imply that, as a result of disasters that hit ports, tradable sectors' stock returns decline by 0.36% more than those of non-tradable sectors in the upstream country and by 0.27% more in the downstream country. Additionally, for these disasters, the returns of the automobile sector decline by 0.39% more than those of the real estate sector in the upstream country, while they decline by 0.32% more in the downstream country. Columns 9 to 12 of Table 8 show that, for the disasters that did not hit ports, tradable sectors in foreign countries do not suffer significantly greater losses than non-tradable sectors.

Cross-country Heterogeneity in Climate Disaster Spillover Effects Appendix Table D.4 illustrates how institutional factors in home and foreign countries affect the foreign

[49] We multiply the estimated coefficients with the exposure measure of an average disaster that is summarized in Table A.1.

[50] We multiply the estimated coefficients with the exposure measure of an average disaster that is summarized in Table A.1 and the time-average of sector tradability to calculate size. The time-average of automobile sector's tradability, TD^{AUTMB}, is 0.647, and the time-average of real estate sector's tradability, TD^{RLEST}, is 0.019.

Table 8: **Impact of Climate Disasters on Tradable Sectors in Upstream and Downstream Stock Markets**

Dependent Variable: Cumulative Abnormal Return												
	Full Sample				Hit Port				Didn't Hit Port			
	Upstream		Downstream		Upstream		Downstream		Upstream		Downstream	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Exposure to Foreign Disaster	123.0	161.3	-153.4	-187.9	400.5**	448.6***	-1,012***	-1,053***	-133.6	-102.0	-73.47	-91.49
	(105.1)	(108.5)	(144.1)	(139.8)	(167.5)	(171.3)	(289.8)	(277.3)	(153.6)	(158.6)	(199.6)	(198.8)
Exposure to Foreign Disaster	-321.3***		-262.8**		-494.4***		-581.0**		-172.9		-191.8	
$\times TS^s$	(114.2)		(128.0)		(158.3)		(256.2)		(159.1)		(152.1)	
Exposure to Foreign Disaster		-550.2***		-376.3*		-869.4***		-1,075**		-316.0		-266.8
$\times TD^s$		(174.9)		(209.1)		(256.5)		(452.0)		(235.3)		(246.2)
Observations	12,795	12,795	12,795	12,795	5,235	5,235	5,235	5,235	7,560	7,560	7,560	7,560
Midstream Cou. FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Downstream Cou. FE	No	No	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes
Upstream Cou. FE	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes	No	No
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean Dep. Var	-0.00918	-0.00918	-0.00758	-0.00758	-0.00959	-0.00959	-0.00899	-0.00899	-0.00890	-0.00890	-0.00661	-0.00661
R^2	0.118	0.118	0.107	0.107	0.104	0.104	0.0949	0.0949	0.125	0.125	0.114	0.114

Description: This table presents the estimated parameters of model 11. TS^s is a dummy variable that equals 1 if the sector belongs to basic material, industrial production, or consumer goods sectors. TD^s equals sector s' total trade divided by the sector's total GDP on the world level. The sample is composed of main trade partners of the countries hit by a large climate disaster. We pool all sectors' estimated cumulative abnormal returns to investigate the heterogeneity across sectors. We measure the cumulative abnormal returns with their values at 80 trading days after the beginning of the climate disaster. Standard errors are presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

stock market losses due to climate disasters. In particular, we consider the following two factors: (1) financial integration, measured with the total value of assets and liabilities divided by annual GDP, and (2) whether the home country or the trade partner country is an emerging market economy. A country that is more financially integrated is expected to have a more advanced financial sector and therefore be more financially stable. Additionally, emerging market economies might be more vulnerable to home and foreign climate disasters.

We find that if the countries hit by climate disasters or their trade partners have a more developed financial system, the disasters will incur smaller stock market valuation losses in the upstream and downstream countries (Columns 1, 3, and 7). As a result, a resilient financial system may be able to reduce the magnitude of trade disruptions and the adverse effects of climate disasters on foreign stock markets. Additionally, climate disasters result in greater losses if the downstream countries are emerging markets.

These evidence is consistent with what we found in Table A.5 for the real economy: economically or financially less developed countries are more susceptible to disruptions in supply and demand caused by foreign climate disasters.

Estimating Welfare Losses based on Stock Market Losses According to Amiti et al. (2021), a country's consumer welfare can be estimated using information regarding sectoral stock market returns using the following formula:[51]

$$\text{dlog}(C_k) = \sum_{s=1}^{S} \frac{w_k^s L_k^s}{GDP_k} \text{dlog}(r_k^s) + \sum_{s=1}^{S} \frac{r_k^s K_k^s}{GDP_k} \text{dlog}(r_k^s) - \text{dlog}(P_k),$$

[51] Greenland et al. (2020) uses a similar method.

where $w_k^s L_k^s$ and $r_k^s K_k^s$ denotes the labor and capital income in sector s, country k. GDP_k denotes country k's GDP. $\text{dlog}(P_k)$ denotes the change in consumer price index.[52]

Amiti et al. (2021) show that, based on the assumptions of constant elasticity of substitution between labor and capital in a representative firm's production function, and the firm's short-run capital is fixed, the change in country-level wages is equal to the weighted average of sectoral stock returns, in which the weight represents the sectoral employment share. The change in a country's income, which equals the sum of labor income and capital income, can therefore be calculated using only capital returns. The country's consumption change equals its income change minus inflation.

Based on the event study approach described in Section 5.1, we collect country-sector level stock market returns due to foreign climate disasters and present them in Figures D.3 and D.4. We show that climate disasters do not significantly affect CPI in main upstream and downstream countries (Figures A.7).

Combining these inputs, we find that an average climate disaster reduces consumption by 0.22$\%$ in the main downstream country (95$\%$ confidence interval: $[-0.53\%, 0.08\%]$ and by 0.35% in the main upstream country (95% confidence interval: $[-0.69\%, -0.01\%]$). These estimates are comparable to the impacts that we directly estimated with the event study on the real economy and data on consumption directly in Section 4.6.

Firm-level Evidence We investigate firm-level financial market responses to foreign climate disasters using databases of Chinese firms.[53] We obtain Chinese industrial firms' financial and trade data from China Industrial Enterprise Database and China Custom Import and Export Database.[54] Since we study the financial market, we focus on publicly listed companies and match them to stock price data obtained from the Wind Financial Terminal.

We measure the exposure of a firm to foreign climate disasters using a method similar to that used in the analysis of the real economy in Section 3. For each climate disaster d that happens in country i, we identify all Chinese firms (denoted with f) that source from

[52]In fact, this formula implies that: $\text{dlog}(C_k) = \sum_{s=1}^{S} \frac{GDP_k^s}{GDP_k} \text{dlog}(r_k^s) - \text{dlog}(P_k)$, which shows that the change in consumption equals a weighted average of the changes in sectoral stock returns (weights equal to the sectoral GDP share) minus inflation.

[53]Since other firm-level outcomes that we have access to are only available at the annual level, we focus on the financial market response.

[54]The Chinese Industrial Enterprise Database is available at the firm-year level, while the Chinese Custom Import and Export Database is available at the firm-product-year level. We match these databases based on firm names, sectors, and addresses at the firm-year level. The method of matching is described in detail at Li (2021).

country i in the previous year $y-1$.[55] We estimate the impact of climate disasters on these downstream firms with the following specification:[56]

$$y_{f,d,t} = \sum_{m=-\bar{t}}^{\bar{t}} \beta_m^{down} \mathbb{I}_t \{m \text{ Months After Climate Disaster } d\} \frac{Damage_{i,d} \times S_{f,i,y-1}}{Revenue_{f,y-1}} + \alpha_{f,d} + \lambda_{f,d} + \epsilon_{f,d,t}, \tag{12}$$

where $\frac{Damage_{i,d} \times S_{f,i,y-1}}{Revenue_{f,y-1}}$ measures downstream firm f's exposure to the disaster. $S_{f,i,y-1}$ denotes the output share of country i to Chinese firm f. $Damage_{i,d} \times S_{f,i,y-1}$ measures the loss in sales from country i to Chinese firm f, and such loss is normalized with the firm's revenue in the previous year. The event window runs from 4 months before the disaster start date to 4 months after the disaster start date. $y_{f,d,t}$ denotes the stock price of firm f at time t around disaster d.

To study the effect on upstream firms, we estimate:

$$y_{f,d,t} = \sum_{m=-\bar{t}}^{\bar{t}} \beta_m^{up} \mathbb{I}_t \{m \text{ Months After Climate Disaster } d\} \frac{Damage_{i,d} \times \pi_{i,f,y-1}}{Revenue_{f,y-1}} + \alpha_{f,d} + \lambda_{f,d} + \epsilon_{f,d,t}, \tag{13}$$

where $\frac{Damage_{i,d} \times \pi_{i,f,y-1}}{Revenue_{f,y-1}}$ equals the loss in demand by country i from upstream firm f, normalized with the firm's revenue in the previous year.

Appendix Figure D.5 shows that foreign climate disasters significantly reduced the stock market prices of Chinese firms, regardless of whether they are a supplier of customer of this foreign country. After two months of the disaster, stock prices drop by 0.1% in an average downstream firms and by 0.02% in an average upstream firm.[57]

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

Climate change increases the likelihood of larger and more frequent climate disasters in the long run (BlackRock 2019, Woetzel et al. 2020). These risks differ across countries. Tropical countries, for example, may experience more heatwaves than countries in middle or high latitudes. Sea-level rise and flood risks may be greater in coastal countries than

[55] Since the Chinese Custom Import and Export Database is available only on the year level, we use variables in the year prior to the disaster to construct the exposure measure.

[56] In this specification, the control group is the Chinese firms that do not source from country i.

[57] These magnitudes are less than those found at the country-sector level, likely because we are investigating the effects on average of all Chinese firms that source from and sell to the disaster-affected foreign country.

in inland countries. Through importing and exporting relationships, the major trading partners of high climate risk countries are exposed to these foreign climate risks. Based on the findings in Section 5, rational investors anticipate that when these risks are realized, the stock returns in downstream and upstream countries will be adversely affected. Therefore, they should price foreign climate risks into the valuation of their portfolios and reduce the valuation of the assets that are more affected by foreign climate risks.

In order to measure foreign climate risks, we adapt the measure of foreign climate disasters that we introduced in Section 3.2.2. We measure the extent a downstream country k is exposed to foreign climate risks in year y, by weighting the climate risks in all other countries with the share of output that another country i sells to k:

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

where R_i denotes the climate risks in country i. If $S_{k,i,y} = 0$, $\forall i \neq k$, no foreign country is selling to country k. In this case, $D_{k,y} = 0$, which implies that the downstream country k is not 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.

In a similar manner, we determine the foreign climate risk exposure of an upstream country as follows. In our sample, all countries are also exposed to foreign climate risks through the upstream spillovers channel:

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

On a sector level, we examine how exposures to foreign climate change risks impacts stock market P/E ratios in the home country. We focus on stock market P/E ratios because both climate risks and P/E ratios are long-term issues. 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 can be explained by 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).

We run the following regression sector by sector to obtain the residual P/E ratio, $\widehat{RPE}^{s}_{i,y}$ – the part of the stock market valuation that cannot be explained by standard valuation metrics:

$$PE^s_{i,y} = a^s_0 + a^s_1 r^f_{i,y} + a^s_2 EXPFE_{i,y} + a^s_3 ERP_{i.y} + RPE^s_{i,y}. \tag{16}$$

Next, we regress the residual P/E ratios on the exposures to foreign risks in downstream and upstream countries with a pooled regression of all sectors in year 2018:[58]

$$\widehat{RPE}^{s}_{k} = \ b \times D_k + \zeta^s + \epsilon^s_k, \tag{17}$$

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

$$\widehat{RPE}^{s}_{j} = \ b \times U_j + \zeta^s + \epsilon^s_j, \tag{18}$$

Columns 1–2 of Table 9 show that country-sector level stock market P/E ratio is negatively associated with foreign climate risk exposure 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 0.042-0.048 standard deviation decline in the P/E ratio. An interquartile increase in the exposure to foreign risks is associated with a reduction in the P/E ratio of about 7.0 for both downstream and upstream countries.

Table 9: **Association between Exposure to Foreign Climate Risks and Home-country P/E Ratio**

VARIABLES	(1) Up pooled	(2) Down pooled	(3) Up Interaction	(4) Down interaction	(5) Up placebo	(6) Down placebo	(7) Up placebo interaction	(8) Down placebo interaction
Exposure to Foreign Climate Risk	-143.2***	-146.5***	10.75	15.54	18.88	21.72	-5.837	-10.13**
	(39.44)	(53.65)	(23.64)	(22.87)	(32.04)	(37.77)	(7.915)	(4.582)
Exposure to Foreign Climate Risk			-349.0***	-375.8***			56.03	72.21
× Tradability			(106.8)	(119.4)			(77.63)	(92.93)
Observations	1,235	1,235	1,235	1,235	1,235	1,235	1,235	1,235
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean Dep. Var	-43.83	-43.83	-43.83	-43.83	-43.83	-43.83	-43.83	-43.83
R^2	374.8	374.9	374.4	374.6	375.5	375.5	375.6	375.5
Δ_{sd}	-0.0488	-0.0424	-0.0216	-0.0186	0.0115	0.0127	-0.00305	-0.00530
Δ_{interq}	-7.029	-7.185	-3.111	-3.154	2.489	3.236	-0.663	-1.354

Description: This table shows the association between home-country residual P/E ratio and upstream and downstream exposures to foreign climate risks. Columns 1 and 2 show the impact of upstream and downstream foreign climate risk exposures for all sectors. Columns 3 and 4 add to Columns 1 and 2, respectively, the interaction between upstream and downstream foreign climate risk exposures and the importing and exporting tradability. Columns 5 and 6 present the result with placebo upstream and downstream foreign exposures–openness to trade. Columns 7 and 8 add the interaction between openness to trade and importing and exporting tradability. In Columns 1-2 and 5-6, Δ_{sd} refers to the change in the standard error of the dependent variable associated with one standard deviation increase in the independent variable, Δ_{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 3-4 and 7-8, Δ_{sd} refers to the change in the standard error of the dependent variable associated with one standard deviation increase in the exposure to foreign climate risks for sectors with median readability, Δ_{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. Robust Standard errors in parentheses are clustered at country level. *** p<0.01, ** p<0.05, * p<0.1.

We show that international trade is the key spillover channel of foreign climate risks

[58] Climate risk data for 2018 is the most recent available, and a country's climate risk does not change significantly over time.

by documenting that tradable sectors are more negatively associated with the same foreign climate risks than non-tradable sectors. To formally test this hypothesis, we include the interaction between sector tradability and the exposures to foreign climate risks in downstream countries as the regressor:

$$\widehat{RPE}_k^s = b\,D_k \;+\; c\,TD^s \times D_k + \zeta^s + \epsilon_k^s. \tag{19}$$

We use the following specification for upstream countries:

$$\widehat{RPE}_j^s = b\,U_j \;+\; c\,TD^s \times U_j + \zeta^s + \epsilon_j^s. \tag{20}$$

Columns 3–4 of Table 9 show that, once the interaction term is introduced, the level effects of foreign climate risks become smaller, even insignificant for the downstream countries. 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.[59]

Pooled Regression of All Years and Alternative Fixed Effects Along with the cross-sectional regression that we considered in Equations (17) and (18), we also report the results of a regression that pools all years for which we have the climate change risks data. In these regressions we control year fixed effects and cluster standard errors on the year level. Table D.5 shows that the results remain robust.

Figure D.6 shows the regression coefficients year by year. Correlations between PE ratios and foreign climate risks have become substantially more negative over time.

In Table D.6, we replace the level effects of foreign climate risks in Equations 19 and 20 with country-level fixed effects. Results regarding the interaction terms between foreign climate risk exposures and sector tradability remain robust.

Placebo Tests We show that the negative association between the P/E ratios and exposures to foreign climate risks is not naively 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 equal the

[59]For the sector at the 50th percentile of tradability (food and beverages), a one standard deviation increase in exposures to foreign risks in downstream countries is associated with a 0.0186 standard deviation decline in the P/E ratio. For the sector with the 25th percentile tradability (technology), the number is 0.005. For the sector with the 75th percentile importing tradability (chemicals), the number is 0.058. A one standard deviation increase in the foreign risk exposures in upstream countries is associated with a 0.007, a 0.022, and a 0.064 standard deviation decline for the sector at the 25th (technology), the 50th (food and beverages), and the 75th (chemicals) percentiles of exporting tradability, respectively.

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 $\widetilde{D}_{k,y}$ means country k is more important as a global exporting destination.

The placebo foreign climate risks in upstream countries 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 17, 18, 19, and 20, with their corresponding placebo measures.

Columns 5–6 of Table 9 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 7–8 find that the interaction between the placebo foreign exposures and the tradability measures are not significantly correlated with the P/E ratios in the home country in most cases. This shows that openness to trade alone cannot fully explain the negative association between the home-country P/E ratios and exposure to foreign climate risks.[60] Instead, the key driver for the negative correlation is trading with 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, richer countries and countries with stronger current economic growth. To rule out these confounding channels, we replace climate risks R_i in Equations 17, 18, 19, and 20 with GDP, GDP per capita, GDP growth and per capita GDP growth in respective countries. In Appendix Table D.7, 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 trade openness with these countries. 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.

[60] Standard stock valuation predictors, as described in Equation 16, may already have accounted for the impact of openness to trade, which is a standard macroeconomic performance indicator.

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 a correlation for non-tradable sectors. As climate change increases climate risks in many countries, 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 provide rich evidence which demonstrates 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. The degree to which these effects will be felt depends on whether the climate catastrophes will hit ports and the composition of sectors in the foreign trading partners.

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.[61] The framework is also readily applicable to the cross-border spillover effects of other crises, for exam-

[61] In addition, it would be interesting to construct a quantitative model calibrated to these empirical estimates for assessing the economic effects of climate disasters in general equilibrium. In this paper, we examine how climate disasters affect important trade partners in comparison to their respective control groups. In analyzing the real economy, the control group is defined as the country which is most similar to the climate disaster-affected country but has not been impacted by it. In analyzing the financial market, the control group is the global stock index. Although these control groups are less exposed to the climate disaster, they may still be affected since the global economy is interconnected in numerous ways. In order to understand the total impact of a climate disaster on the main trading partners, it would be useful to build a model that accounts for its effects on the countries in the control group.

ple, COVID-19. The methodology may also be extended to study the spillovers of shocks through other means 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. As a result, this methodology can be further applied to evaluate 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

The analysis we conduct is at the monthly level, whereas the most detailed national GDP statistics are only available at the quarter level. Accordingly, we employ an estimation algorithm that estimates GDP at the monthly level by utilizing more aggregate GDP series and other macroeconomic indices.

First, we obtain several macro indicators in monthly basis from Refinitive Datastream in order to facilitate an interpolation algorithm for estimating a monthly GDP panel. Among the indicators are several indexes related to economic activity, including the industrial production index, the industrial production manufacturing index, and the employment index. In this assumption, these performances of the economy should reflect the gross domestic production. With a higher industrial production index, we can expect a higher gross production. In practice, we assume a linear relationship between GDP and these economic activities.

We proceed in the following steps to estimate a monthly GDP panel. In our analysis, we begin with a raw GDP database that we obtained from IFS and OECD statistics, which consists of quarterly and annual GDP observations for 201 countries. We then combine the macroeconomic activity indexes by country and time with the raw panel. The following functions are used to estimate the monthly GDP. For a country i with GDP_{iq} in Quarter q:

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

$Index_m$ is constructed with multiple macro indexes and estimation is based on an algorithm that prioritizes the availability of data. Specifically, we consider data entries for which industrial production indexes are available. We then estimate GDP in months where another index, i.e. industrial manufacturing index, is available after estimating GDP in these months. In the event that neither the industrial production index nor the industrial production manufacturing index is available, we interpolate with the employment index. If any month within a quarter has missing values, we mark the economic performance index as unavailable for that quarter. This ensures that we only use one type of index to decompose GDP into monthly values for a given quarter.

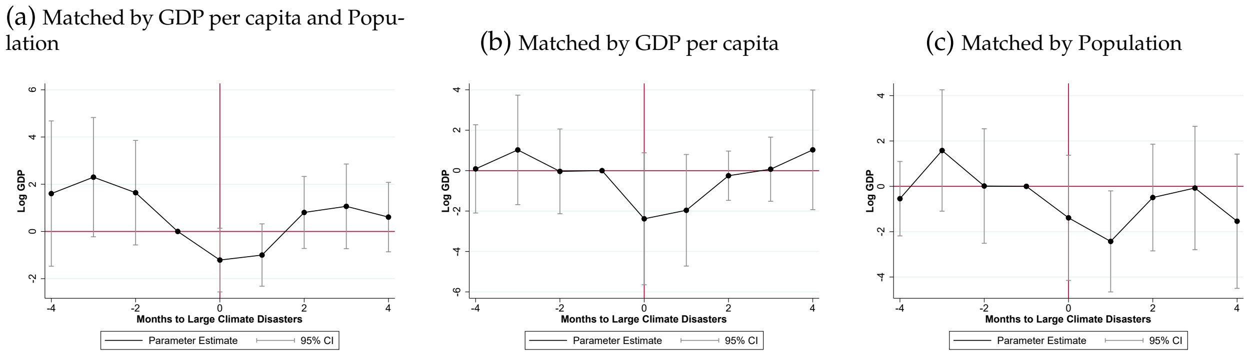
A.2 Construction of the Stacked Dataset

For the event study, we analyzed 430 large climate disasters, i.e. 430 events. According to the stacked DID method, we must estimate treatment effects separately for each event. As a first step, we construct 430 event-specific monthly panels. Next, we stack these datasets in the relevant time period and estimate a regression model with individual-event and time-event fixed effects.

An event d-specific dataset includes the treated country and its best-matched clean control country, each for a nine-month period (t=$-4, ..., 4$). The disaster shock takes place at t $= 0$. Identifying the best-matched clean controls involves the following steps. To begin with, we separate the datasets into two groups: the treatment group and the control group. All disaster events are included in the treatment group, which includes 9×430 observations. The control group includes all remaining observations. As a second step, we estimate a propensity score for each observation, using the population and GDP of the previous year as dependent variables. Third, for each disaster d, let's say the disaster occurred in the year y_d, month m_d, we refine the control group to include only observations made at the same time, year y_d, month m_d. According to the propensity score, we determine the closest neighbor of the treated country among the refined control observations. With 430 in treated-control pairs at $t = 0$, we complement the datasets by including all 9-month observations (t=$-4, ..., 4$) 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. The coefficients for all three figures are negative during the first two months following the disaster, indicating that the results are robust in spite of the different matching methods used.

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



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: **Damages as a Percentage of GDP by Type of Climate Disaster**

Variable	N	Mean	St. Dev.	Min	Max
Storm					
Damage Ratio (%)	134	1.065	3.633	0.000	31.403
Flood					
Damage Ratio (%)	283	0.368	0.927	0.000	8.250
Extreme Temperature					
Damage Ratio (%)	6	0.175	0.144	0.000	0.359
Landslide					
Damage Ratio (%)	3	1.205	1.443	0.162	2.851
Drought					
Damage Ratio (%)	4	0.175	0.14391	0.000	0.359

Description: This table summarises the information about climate disasters by different disaster types.

Table A.3: **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 × 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.4: **Impact of Foreign Climate Disasters on 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
× 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 × 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.5: **Impact of Foreign Climate Disasters on Country's Production: Impact on the 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	-4,175		-385.0	
× Emerging Market	(3,051)		(430.8)	
Downstream Emerging Market		-0.00682		
		(0.0271)		
Exposure to Foreign Disaster		-9,471*		
× Downstream Emerging Market		(5,379)		
Upstream Emerging Market				0.0121
				(0.0149)
Exposure to Foreign Disaster				-979.6***
× Upstream Emerging Market				(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.6: **Gravity Effect on Disaster Spillovers**

VARIABLES	(1) Log Downstream GDP	(2) Log Downstream GDP	(3) Log Downstream GDP	(4) Log Downstream GDP	(5) Log Upstream GDP	(6) Log Upstream GDP	(7) Log Upstream GDP	(8) Log Upstream GDP
Treated	-0.0879*	0.00294	0.00123	0.000863	-0.0388	-0.00432	0.00736	0.0118
	(0.0484)	(0.00661)	(0.00755)	(0.00822)	(0.0451)	(0.00763)	(0.00806)	(0.00852)
Treated	0.0103*				0.00467			
× Log Distance	(0.00560)				(0.00561)			
Treated		-0.0267				0.0213		
× Contiguity		(0.0264)				(0.0178)		
Treated			-0.00463				-0.0302**	
× Language			(0.0156)				(0.0137)	
Treated				-0.00307				-0.0367**
× Legal System				(0.0144)				(0.0139)
Observations	3,186	3,186	3,186	3,186	3,186	3,186	3,186	3,186
Cou. X Dis. FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time X Dis. FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Dis.	Dis.	Dis.	Dis.	Dis.	Dis.	Dis.	Dis.
Mean Dep. Var	12.16	12.16	12.16	12.16	11.96	11.96	11.96	11.96
R^2	0.0759	0.0760	0.0761	0.0761	0.0704	0.0703	0.0702	0.0701

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 countries observed 4 months around the disaster shock. Only disasters that affect at least one local port are included in this sample. "Treated" is an indicator indicating whether the observation belongs to the treatment group. "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. "Language" is an indicator which equals 1 if the downstream/upstream country speaks the same language as the disaster-hit home country. "Legal System" is an indicator which equals 1 if the downstream/upstream country shares the same legal system origin as 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. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A.7: **Impact of Climate Disasters: Whether Hit Populous Region**

VARIABLES	(1) Log Midstream GDP	(2) Log Midstream GDP	(3) Log Downstream GDP	(4) Log Downstream GDP	(5) Log Upstream GDP	(6) Log Upstream GDP
Exposure to Disaster	-1.031***	1.457	-1,417***	-429.5	-869.7***	4.387
	(0.191)	(3.213)	(172.9)	(544.7)	(245.1)	(174.8)
Observations	1,440	1,746	1,440	1,746	1,440	1,746
Sample	Populous	Non Populous	Populous	Non Populous	Populous	Non Populous
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	8.416	12.16	12.16	11.96	11.96
R^2	0.161	0.136	0.0724	0.0787	0.0657	0.0736

Description: This table presents the size of disaster spillovers in regarding to whether hit populous regions. We divide the disasters into two subgroups by the median of the disaster's affected population divided by the total population of the country. We constrain the sample to the countries observed 4 months around the disaster shock. Only disasters that affect at least one local port are included in this sample. In Columns 1 - 2, "Exposure to Disaster" is the monetary loss in the midstream country divided by its GDP. In Columns 3 - 6, "Exposure to 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 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.8: **Disaster Effect on Foreign Country Production: Excluding Neighboring Countries**

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	-589.9***	-407.7*	-760.1*	-673.3**	-555.2***	-240.7
	(89.18)	(226.7)	(397.2)	(322.5)	(77.86)	(146.9)
Observations	6,354	6,354	2,808	2,808	3,546	3,546
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	12.25	11.96	12.4	12.19	12.13	11.77
R^2	0.0824	0.0756	0.0748	0.072	0.0879	0.0784

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. We exclude the countries that are neighbor with the disaster-hit country. 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 × 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. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A.9: **Disaster Effect on Foreign Country Production: Including Both Upstream and Downstream Exposure Measure**

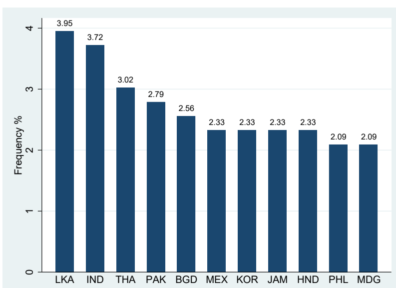
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Log Downstream GDP	Log Downstream GDP	Log Downstream GDP	Log Upstream GDP	Log Upstream GDP	Log Upstream GDP
Exposure to Disaster by Export	-1,046**	-3,908	-1,470	839.0*	403.9	1,968**
	(451.0)	(2,508)	(1,031)	(499.1)	(863.2)	(891.9)
Exposure to Disaster by Import	835.4	2,805	1,281	-741.1**	-712.1	-1,285**
	(529.6)	(2,122)	(1,315)	(358.1)	(533.3)	(498.7)
Observations	7,740	3,186	3,834	7,740	3,186	3,834
Sampe	Full Sample	Hit Port	Exclusion	Full Sample	Hit Port	Exclusion
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	12.36	12.02	11.96	12.21	11.70
R^2	0.0842	0.0758	0.0898	0.0747	0.0703	0.0745

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. "Exposure to Foreign Disaster by Export" is the monetary loss in the midstream country divided by the trade partner country's yearly GDP $\times$ output share of the home country on the trade partners. "Exposure to Foreign Disaster by Import" is the monetary loss in the midstream country divided by the trade partner country's yearly GDP $\times$ expenditure share of the home country on the trade partners. Log GDP is the log of gross domestic production. In Columns 1 and 4, we report results from the full sample. In Columns 2 and 5, we report results from the disasters that hit at least one port. In Column 3 and 6, we exclude the observations that the main downstream and the main downstream countries of the midstream are the same. Standard errors are two-way clustered at the country-disaster level. Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

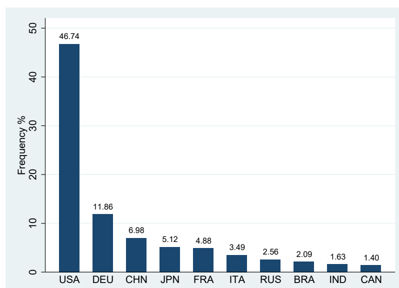
A.4 Additional Figures

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

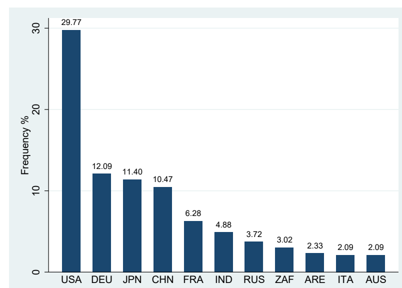
(a) Most Frequent Disaster-hit country



(b) Most Frequent Main Downstream Country



(c) Most Frequent Main Upstream Country

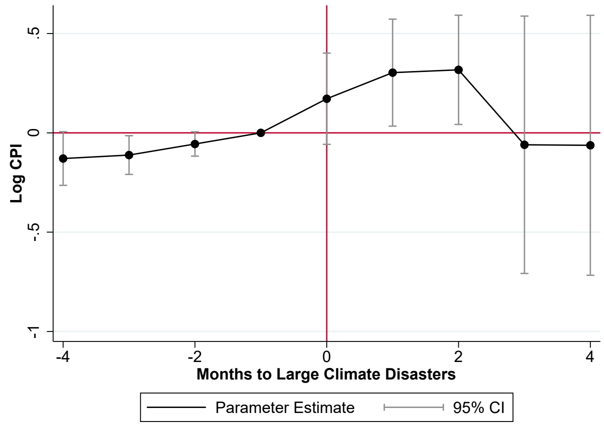


Description: Figure (a) shows the top 10 countries most frequently hit by a large climate disaster in our sample. Figure (b) shows the top 10 countries that disaster-hit countries most frequently export most to. Figure (c) shows the top 10 countries that disaster-hit countries most frequently import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

Figure A.3: **Distribution of Climate Disasters and Ports**

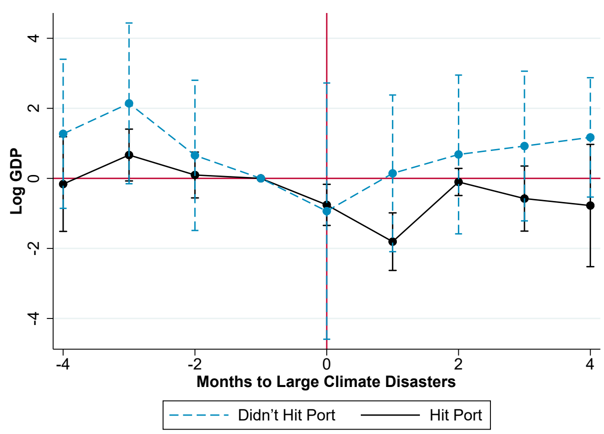
Description: This figure shows the geographical distribution of the climate disasters and ports studied in our main sample. The red circle indicates the normalized size of the disaster area.

Figure A.4: **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.

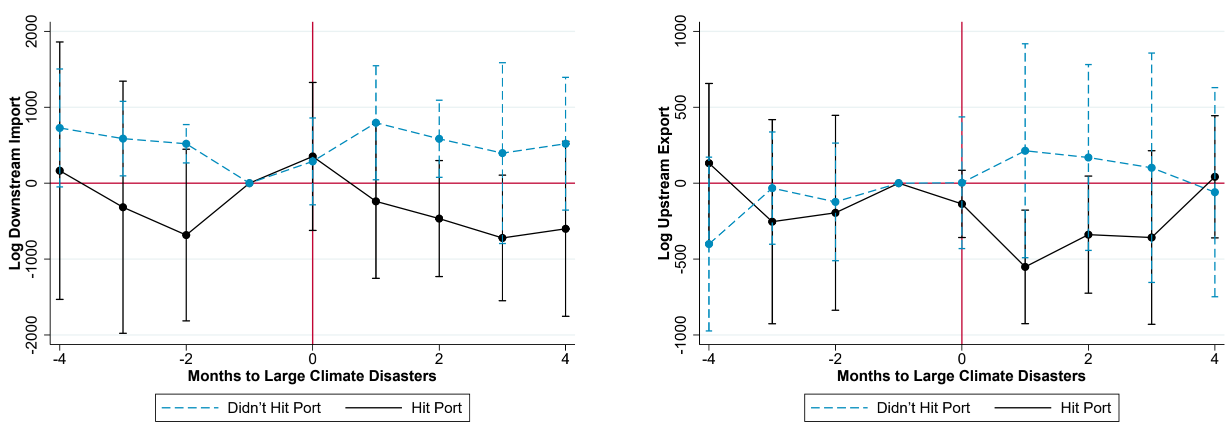
Figure A.5: **Impact of Climate Disasters on Midstream Production by Whether They Hit Port**



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

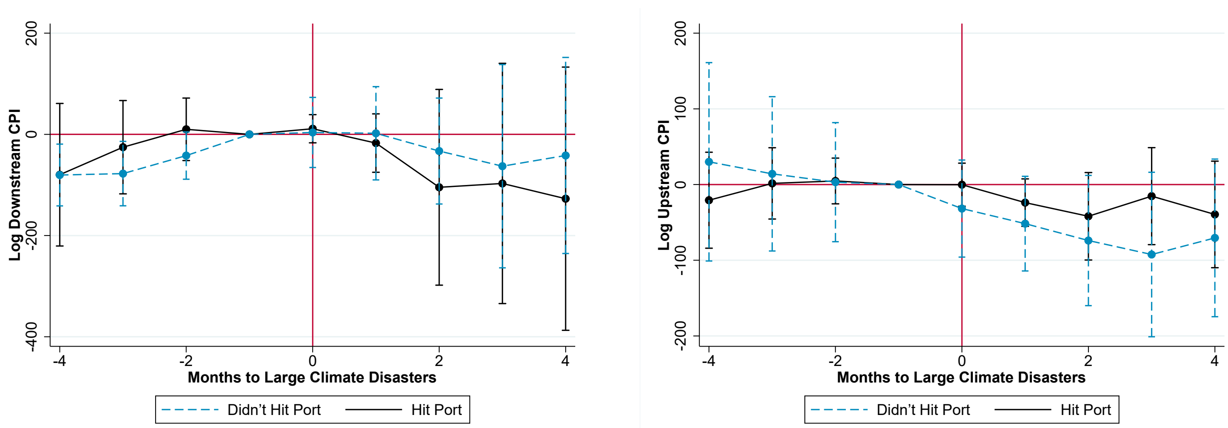
(a) Downstream Total Imports (b) Upstream Total Exports



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

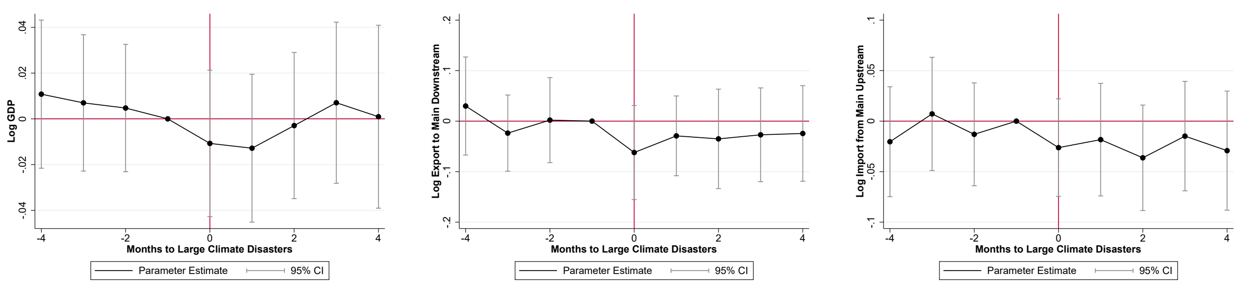
(a) Downstream Price (b) Upstream Price



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

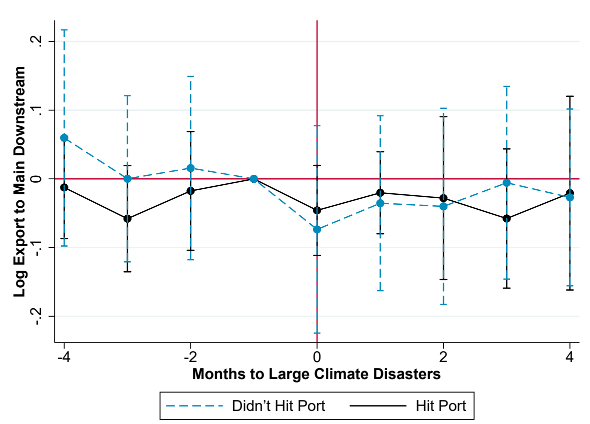
(a) GDP (b) Export to Main Downstream (c) Import from Main Upstream



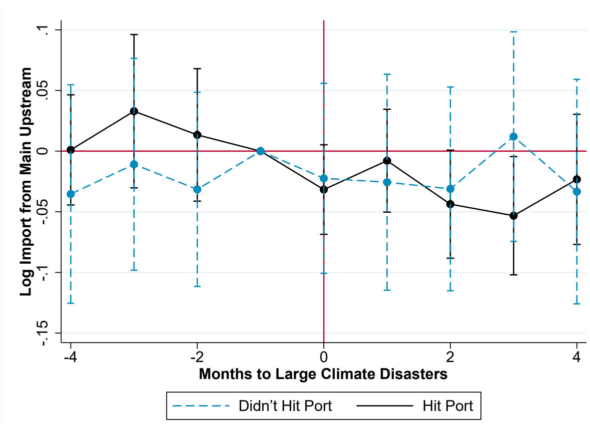
Description: This figure contains the coefficients estimated from the stacked event-study model 1. We replace the independent variable with a dummy indicating whether a disaster has attached the country. The x-axis contains the number of months to the disaster's starting date. GDP data is obtained and 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.9: **Disaster Spillover Effect: Using Dummy as Independent Variable**

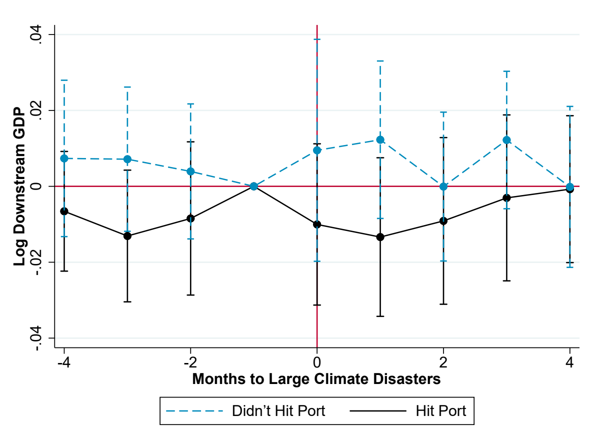
(a) Export to Main Downstream



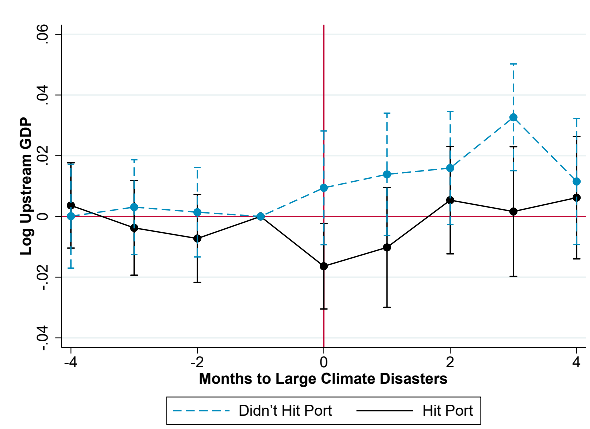
(b) Import from Main Upstream



(c) Downstream GDP



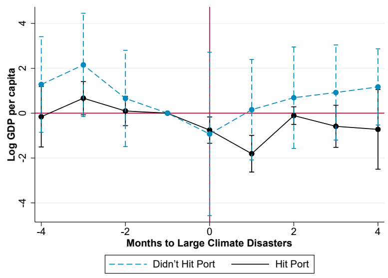
(d) Upstream GDP



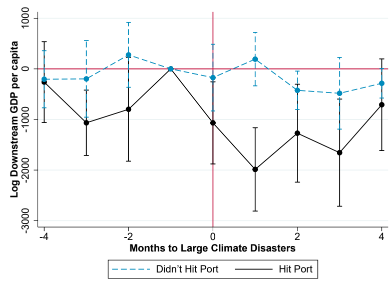
Description: This figure contains the coefficients estimated from the stacked event-study model 1, 3 and 5. We replace the independent variable with a dummy indicating whether a disaster has attached the country. The x-axis contains the number of months to the disaster's starting date. GDP data is obtained 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.10: **Impact of Climate Disasters on GDP per capita**

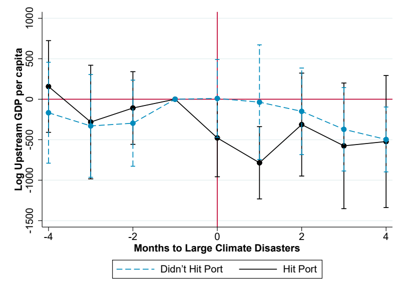
(a) Midstream



(b) Downstream



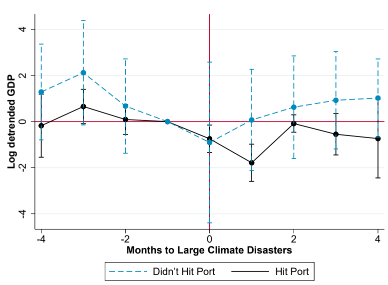
(c) Upstream



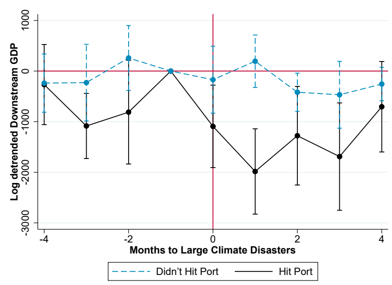
Description: This figure contains the coefficients estimated from the stacked event-study model 1, 3 and 5. The x-axis contains the number of months to the disaster's starting date. GDP data is obtained and estimated based on IMF and OECD statistics. The sample is composed of countries hit by a large 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.11: **Impact of Climate Disasters on GDP: Detrended and Seasonally Adjusted**

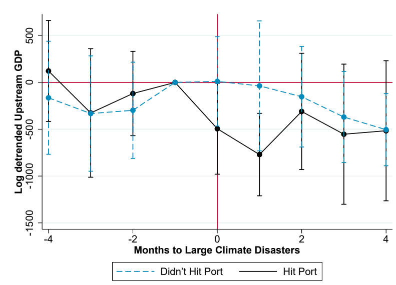
(a) Detrended Midstream



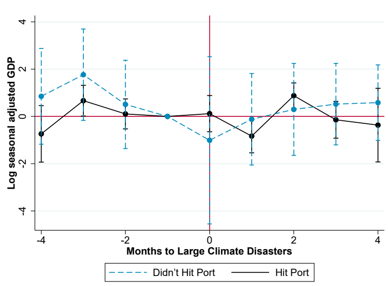
(b) Detrended Downstream



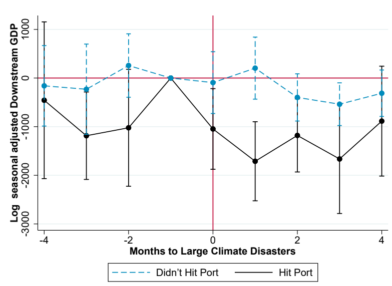
(c) Detrended Upstream



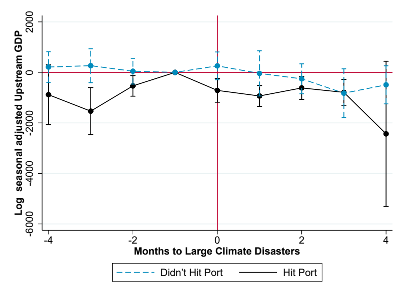
(d) Seasonally Adjusted Midstream



(e) Seasonally Adjusted Downstream



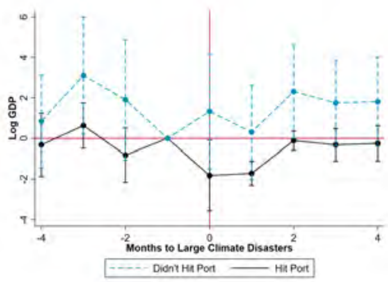
(f) Seasonally Adjusted Upstream



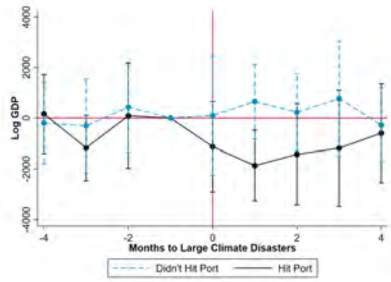
Description: This figure contains the coefficients estimated from the stacked event-study model 1, 3 and 5. The x-axis contains the number of months to the disaster's starting date. GDP data is obtained and estimated based on IMF and OECD statistics. Figure (a), (b), and (c) use linear-detrended GDP 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.12: **Impact of Climate Disasters on GDP: Demeaned and Detrended Damage Measures**

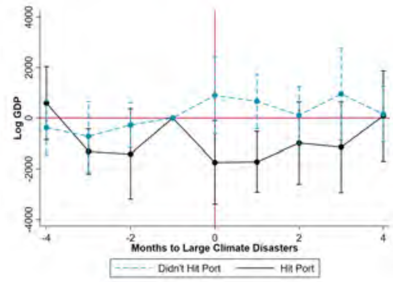
(a) **Demeaned Disaster on Midstream**



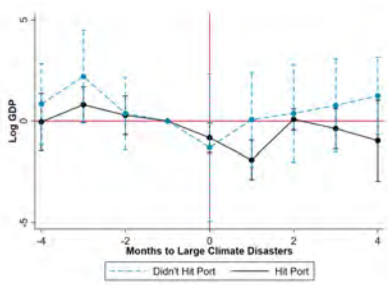
(b) **Demeaned Disaster on Downstream**



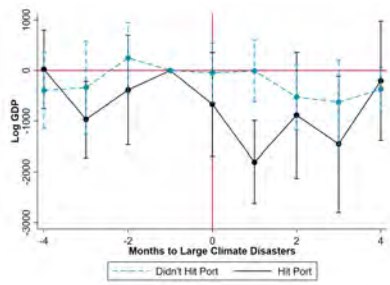
(c) **Demeaned Disaster on Upstream**



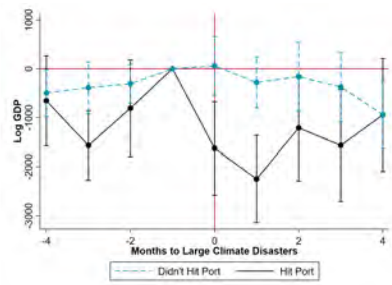
(d) **Detrended Disaster on Midstream**



(e) **Detrended Disaster on Downstream**



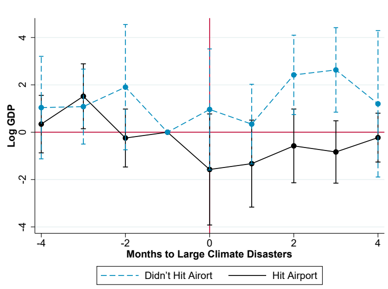
(f) **Detrended Disaster on Upstream**



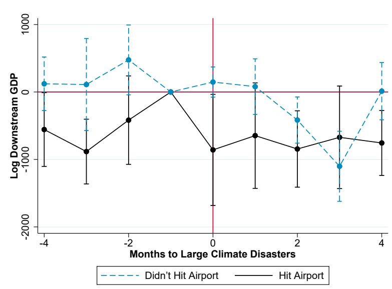
Description: This figure contains the coefficients estimated from the stacked event-study model 1, 3 and 5. The x-axis contains the number of months to the disaster's starting date. GDP data is obtained and estimated based on IMF and OECD statistics. Figure (a), (b), and (c) use linear-demeand damage measure as independent variable to correct for normal disaster occurrences. Figure (d), (e), and (f) use linear-detrend damage measure as independent variable to correct for anticipated increases in disaster occurrences. 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.13: **Impact of Climate Disasters on GDP by Whether They Hit Airport**

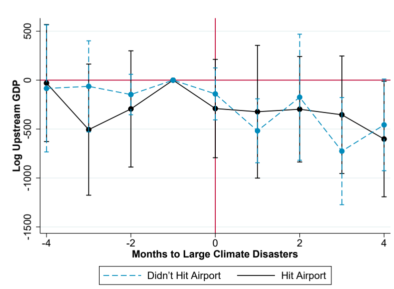
(a) **Midstream**



(b) **Downstream**



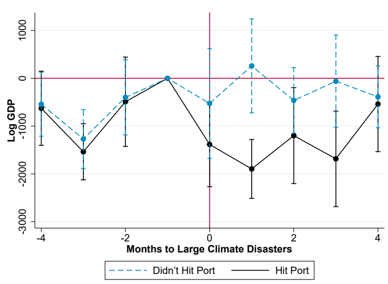
(c) **Upstream**



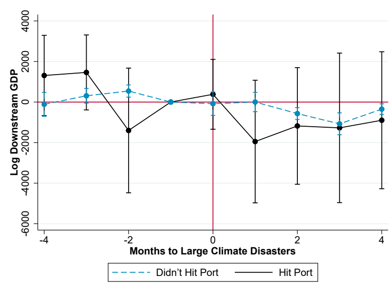
Description: This figure contains the coefficients estimated from the stacked event-study model 1. The x-axis contains the number of months to the disaster's starting date. GDP data is obtained and estimated based on IMF and OECD statistics. The sample is composed of countries hit by a large climate disaster and their control pairs. We constrain the sample to the set of countries observed 4 months around the disaster shock. 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.14: **Impact of Foreign Climate Disasters on GDP by Whether the Main Downstream and the Main Upstream Countries Are the Same**

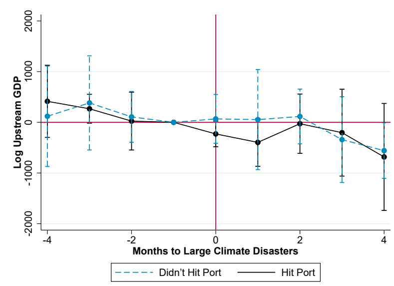
(a) Both Main Downstream and Main Upstream



(b) Only Main Downstream



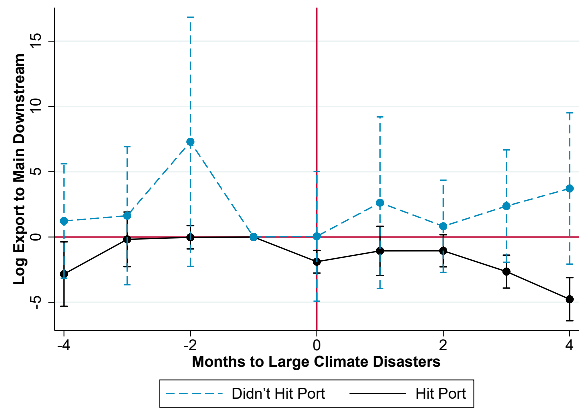
(c) Only Main Upstream



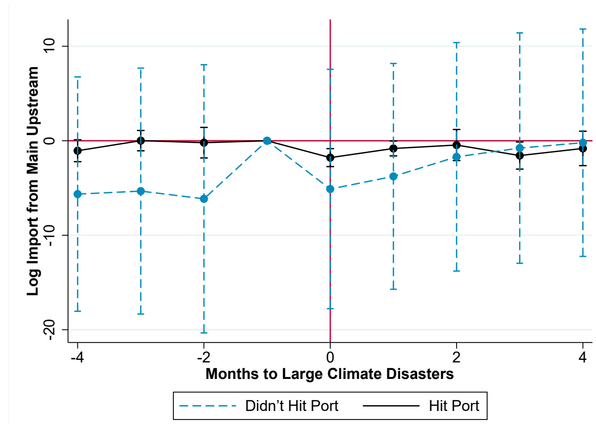
Description: This figure contains the coefficients estimated from the stacked event-study model 1. The x-axis contains the number of months to the disaster's starting date. GDP data is obtained and estimated based on IMF and OECD statistics. The sample is composed of countries hit by a large climate 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.15: **Impact of Climate Disasters on Bilateral Trade by Whether the Main Downstream Is Also the Main Upstream**

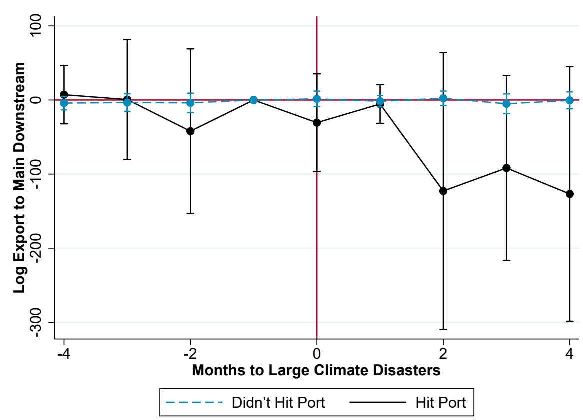
(a) Both Main Downstream and Main Upstream: Midstream Export to Downstream



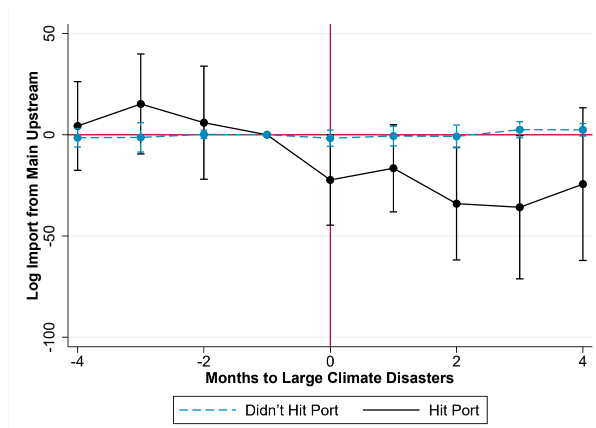
(b) Both Main Downstream and Main Upstream: Midstream Import from Upstream



(c) Only Main Downstream: Midstream Export to Downstream



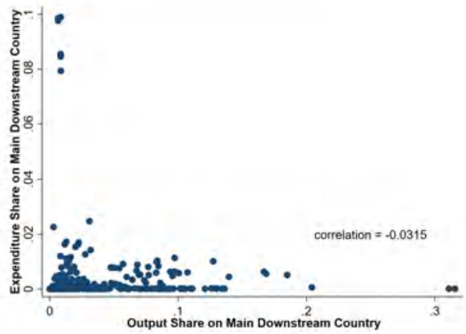
(d) Only Main Upstream: Midstream Import from Upstream



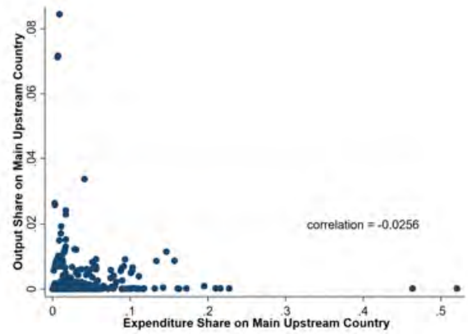
Description: This figure contains the coefficients estimated from the stacked event-study model 1. The x-axis contains the number of months to the disaster's starting date. Trade data is obtained from IMF DOT statistics. The sample is composed of countries hit by a large climate disaster and their control 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.16: **Correlation between Expenditure and Output Shares among Trade Partners**

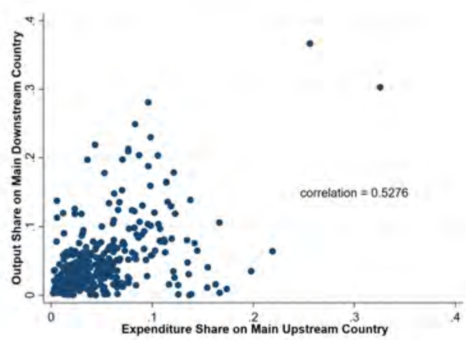
(a) Shares on Main Downstream Country



(b) Shares on Main Upstream Country



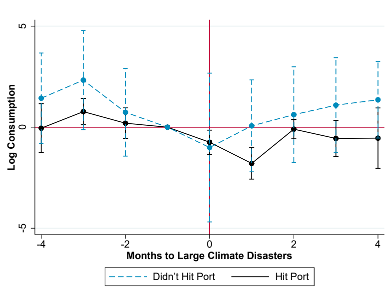
(c) Both Main Downstream and Upstream Country



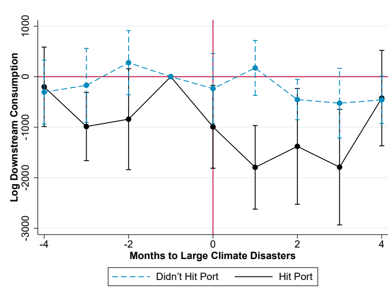
Description: These figures plot the correlation between trade related shares among trade partners. Subfigure (a) plots the relationship between the midstream country's output shares on its main downstream trade partner, and its expenditure share on its main downstream trade partner. Subfigure (b) plots the relationship between the midstream country's expenditure shares on its main downstream trade partner, and its output share on its main downstream trade partner. Subfigure (c) plots the relationship between the midstream country's output shares on its main downstream trade partner, and its expenditure share on its main upstream trade partner.

Figure A.17: **Impact of Climate Disasters on Consumption by Whether They Hit Port**

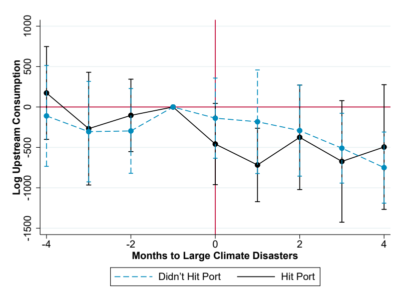
(a) Midstream Consumption



(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 Impact of Trade Disruptions on Cross-border Spillover Effects

In this section, we show how we derived Equation 7 in the text. We start with the trade flow from midstream country i to downstream country k:

$$T_{ki} = P_i Y_i S_{ki},$$

where $P_i Y_i$ denotes country i's total output and S_{ik} is the share of country k in country i's output. Log linearize both sides:

$$\begin{aligned}
\text{dlog}(T_{ik}) &= \text{dlog}(P_i Y_i) + \text{dlog}(S_{ki}) \\
&= \frac{d(P_i Y_i) S_{ki}}{P_i Y_i S_{ki}} + \text{dlog}(S_{ki}) \\
&= \frac{\text{Damage}_i S_{ki}}{P_i Y_i S_{ki}} + \text{dlog}(S_{ki}) \\
&= \frac{\text{Damage}_i S_{ki}}{T_{ki}} + \text{dlog}(S_{ki}).
\end{aligned}$$

Note that in the event of a disaster, the change in a country's output, $d(P_i Y_i)$, equals the monetary damage caused by this disaster, Damage_i.

Furthermore, the downstream country k's production or income equals its expenditure on all suppliers:

$$P_k Y_k = \sum_{i=1}^{N} T_{ki}.$$

Log linearize both side and plug in the expression for $\text{dlog}(T_{ki})$:

$$\begin{aligned}
\text{dlog}(P_k Y_k) &= \sum_{i=1}^{N} \pi_{ki} \, \text{dlog}(T_{ki}) \\
&= \sum_{i=1}^{N} \pi_{ki} \frac{\text{Damage}_i S_{ki}}{T_{ki}} + \pi_{ki} \, \text{dlog}(S_{ki}) \\
&= \underbrace{\sum_{i=1}^{N} \frac{\text{Damage}_i S_{ki}}{P_k Y_k}}_{\text{Supply Shock}} + \underbrace{\pi_{ki} \, \text{dlog}(S_{ki})}_{\text{Trade Openness}},
\end{aligned}$$

where π_{ki} is the expenditure share that downstream country k spends on midstream country i. We apply the identity that links output and trade: $P_kY_k\pi_{ki} = T_{ki}$.

According to this equation, our decomposition involves two main steps. First, we estimate the variation in trade shares due to a climate disaster shock, denoting as $\widehat{d(S_{ki})}$. We fit the cross-sectional DID model 2 using the dynamic output shares and expenditure shares as dependent variable. Table 6 presents the first stage result of our decomposition. Accordingly, we conduct the decomposition exercise on disasters that have affected at least one port, since only these disasters have a significant impact on foreign trade.

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

$$y_{k,d,t} = \underbrace{\beta_1 \times Post_{d,t} \times \frac{\text{Damage}_{i,d} \times S_{k,i,\bar{y}}}{GDP_{k,\bar{y}}}}_{A_1\text{:Supply Shock}} + \underbrace{\beta_2 \times Post_{d,t} \times \frac{\pi_{k,i,t}}{S_{k,i,t}}\widehat{d(S_{k,i,d})}}_{A_2\text{:Trade Openness}} + \alpha_{k,d} + \lambda_{t,d} + \epsilon_{k,d,t}. \tag{B.1}$$

We can decompose the change in upstream GDP due to midstream climate disasters in a similar manner. We start with the trade flow from upstream country j to midstream country i:

$$T_{ij} = P_iY_i\pi_{ij},$$

where P_iY_i denotes country i's total output and π_{ij} is country i's expenditure share on country j. Log linearize both sides:

$$\begin{aligned}
\text{dlog}(T_{ij}) &= \text{dlog}(P_iY_i) + \text{dlog}(\pi_{ij}) \\
&= \frac{d(P_iY_i)\pi_{ij}}{P_iY_i\pi_{ij}} + \text{dlog}(\pi_{ij}) \\
&= \frac{\text{Damage}_i\pi_{ij}}{P_iY_i\pi_{ij}} + \text{dlog}(\pi_{ij}) \\
&= \frac{\text{Damage}_i\pi_{ij}}{T_{ij}} + \text{dlog}(\pi_{ij}).
\end{aligned}$$

Note that in the event of a disaster, the change in a country's income, $d(P_iY_i)$, equals the monetary damage caused by this disaster, Damage_i.

Furthermore, the upstream country i's production equals its sales to all customers:

$$P_j Y_j = \sum_{i=1}^{N} T_{ij},$$

Log linearize both side and plug in the expression for dlog(T_{ij}):

$$\begin{aligned}
\text{dlog}(P_j Y_j) &= \sum_{i=1}^{N} S_{ij}\,\text{dlog}(T_{ij}) \\
&= \sum_{i=1}^{N} S_{ij} \frac{\text{Damage}_i \pi_{ij}}{T_{ij}} + S_{ij}\,\text{dlog}(\pi_{ij}) \\
&= \underbrace{\sum_{i=1}^{N} \frac{\text{Damage}_i \pi_{ij}}{P_j Y_j}}_{\text{Demand Shock}} + \underbrace{S_{ij}\,\text{dlog}(\pi_{ij})}_{\text{Trade Openness}},
\end{aligned}$$

where S_{ij} is the output share that upstream country j sells to midstream country i. We apply the identity that links output and trade: $P_j Y_j S_{ij} = T_{ij}$.

Therefore, in the upstream, we can decompose the change in GDP into contributions by the demand shock and supply chain restructuring according to the following formula:

$$y_{j,d,t} = \underbrace{\beta_1 \times Post_{d,t} \times \frac{\text{Damage}_{i,d} \times \pi_{i,j,\bar{y}}}{GDP_{j,\bar{y}}}}_{A_1\text{:Demand Shock}} + \underbrace{\beta_2 \times Post_{d,t} \times \frac{S_{i,j,t}}{\pi_{i,j,t}} \widehat{d(\pi_{i,j,d})}}_{A_2\text{:Trade Openness}} + \alpha_{j,d} + \lambda_{t,d} + \epsilon_{j,d,t}. \tag{B.2}$$

Table B.1 shows the result for second stage regression. The contribution of supply shock is given by $\frac{\text{Cov}(A_1, A_1+A_2)}{\text{Var}(A_1+A_2)}$, while the contribution of trade disruption is $\frac{\text{Cov}(A_2, A_1+A_2)}{\text{Var}(A_1+A_2)}$. Due to climate disasters, the trade with downstream countries is disrupted but the trade with upstream countries is strengthened. Climate disasters cause 98% of the main downstream country's production loss to result from a reduction in foreign supply, while trade disruptions cause 2% of the loss. In contrast, for the main upstream country, approximately one-third 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 that is induced by the climate disaster.

Table B.1: **Decomposing the Impact of Climate Disasters on Downstream/Upstream GDP into Supply/Demand Shocks and Trade Disruptions**

	(1)	(2)	(3)	(4)
VARIABLES	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 8. 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 A Framework that Studies the Impact of Openness to Trade and International Risk Sharing on Country Risk Exposures

We introduce a model that studies how openness to trade and international risk sharing affects countries' welfare and volatility. For the purpose of generating analytical solutions and demonstrating insights, we examine three scenarios: (1) trade autarky with no international risk sharing;[62] (2) frictionless trade with no international risk sharing; and (3) frictionless trade with perfect international risk sharing. If countries are in trade autarky, they can only consume domestically produced goods. If countries engage in perfect international risk sharing, they trade a stage contingent claim that equates their marginal utility of consumption across countries (see, for example, Cochrane 1991, Backus et al. 1992, Yang 2008). Without loss of generality, we assume that if countries do not share risks, their trade must balance.[63]

We assume all markets are competitive and production is linear in the domestic factor (labor). A country's labor endowment is subject to country-specific shocks and is the only source of uncertainty in the model. We assume countries are symmetric: they are hit by idiosyncratic shocks, but the shock process is the same for all countries. We assume that the state contingent claim is the only way that countries can save. Therefore, if countries do not engage in international risk sharing, they will consume all of their income during the current period.

We assume that the discounted utility of country i's representative consumer equals the following:

$$E_0 \left(\sum_{t=0}^{\infty} \beta^t \frac{C_{it}^{1-\gamma}}{1-\gamma} \right), \tag{C.1}$$

where β is a constant discount factor and γ measures the constant relative risk aversion.

We build on the Armington assumption and assume that each country produces a country-specific tradable good, Y_{it}, using labor and a linear production technology:

$$Y_{it} = L_{it}. \tag{C.2}$$

[62] As a result of trade autarky, since countries neither export nor import, due to the Balance of Payments, they are unable to trade international assets or share international risks.

[63] This is a standard assumption in static international trade models. See, for example, Caliendo and Parro (2015).

Since markets are competitive, we can use w_{it} to denote both the wage and the price of output. The country's labor endowment, L_{it}, is stochastic (possibly affected by climate disasters), which causes the country-specific shock. Assume that L_{it} follows a log-normal distribution with mean μ and standard deviation σ. Assume that L_{it} is i.i.d across countries.

If countries are in trade autarky, they can only consume the country-specific good, and their consumption will equal to production:

$$C_{it} = Y_{it}. \tag{C.3}$$

If countries engage in international trade, their consumption is a CES aggregate of tradable goods from different countries:

$$(C_{it})^{\frac{\theta}{\theta+1}} = \sum_{j=1}^{N} (C_{ijt})^{\frac{\theta}{\theta+1}}, \tag{C.4}$$

where $\theta > 0$ which is a measure of the trade elasticity. Since markets are competitive and trade is frictionless, this implies that the consumer price index is the same across countries and equals to:

$$P_t = \left(\sum_{i=1}^{N} (w_{it})^{-\theta} \right)^{-\frac{1}{\theta}}. \tag{C.5}$$

The trade flow from country i to j equals to:

$$w_{it} y_{jit} = \frac{(w_{it})^{-\theta}}{(P_t)^{-\theta}} P_t C_{jt} \tag{C.6}$$

If countries do not share risks, their consumption will equal to income:

$$P_t C_{it} = w_{it} L_{it}. \tag{C.7}$$

If there is perfect international risk sharing, countries will trade a state contingent claim that pays one unit of capital in each state s_{t+1} (the current state of the world is denoted with s_t). This allows capital to be reallocated across countries. In this case, their budget constraint equals to:

$$P_t C_{it} + \sum_{s_{t+1}} p(s_{t+1}|s_t) Q_i(s_{t+1}|s_t) = w_{it} L_{it} + Q_i(s_t|s_{t-1}) \tag{C.8}$$

We specify the countries' optimization problems under the three scenarios that we discussed:

1. **Trade autarky:** Countries maximize Equation C.1 subject to C.2 and C.3.

2. **Frictionless trade with no international risk sharing:** Countries maximize Equation C.1 subject to C.2, C.4, C.5, C.6, and C.7. Additionally, the market must clear for goods:

$$\sum_{j=1}^{N} y_{jit} = Y_{it}. \tag{C.9}$$

3. **Frictionless trade with international risk sharing:** Countries maximize Equation C.1 subject to C.2, C.4, C.5, C.6, and C.8. Additionally, the market must clear for goods (Equation C.9) and for the state contingent claim:

$$\sum_{i=1}^{N} Q_i(s_{t+1}|s_t) = 0. \tag{C.10}$$

Based on the three scenarios, we can derive the mean, variance, and certainty equivalence welfare for each country.

1. **Trade autarky:** The mean and variance of log consumption equal to the mean and variance of log labor endowment.

$$\begin{aligned} \mathrm{E}(\log(C_{it})) &= \mu \\ \mathrm{Var}(\log(C_{it})) &= \sigma^2. \end{aligned}$$

   The certainty equivalent welfare equals to (Rao and Jelvis 2022):

$$C_{CE} = \mu + \frac{1}{2}\sigma^2(1-\gamma). \tag{C.11}$$

   Under the standard assumption that $\gamma > 1$, higher volatility will lead to consumption equivalent welfare losses (Amiti et al. 2021).

2. **Frictionless trade with no international risk sharing:** Combining Equations C.5, C.6, and C.7 to substitute out prices, we get:

$$C_{it} = L_{it}^{\frac{\theta}{1+\theta}} \left(\sum_{i=1}^{N} (L_i)^{\frac{\theta}{1+\theta}} \right)^{\frac{1}{\theta}}. \tag{C.12}$$

Equation C.12 shows that when countries open to trade, countries are affected by shocks from other countries. The welfare of countries will improve if they can assist other countries in building resilience against climate disasters and climate risks, thereby reducing the mean and volatility of foreign climate disasters.

The consumption in Equation C.12 is strictly higher than the trade autarky case: $L_{it}^{\frac{\theta}{1+\theta}} \left(\sum_{i=1}^{N} (L_i)^{\frac{\theta}{1+\theta}} \right)^{\frac{1}{\theta}} > L_{it}$. This shows that there are gains from openness to trade. Since the products produced by different countries are imperfect substitutes (love-of-variety preferences), it is beneficial for welfare to consume products from different countries.

Since there is no close form for the mean and variance of C_{it} in Equation C.12, we use a first order approximation. Assume countries are symmetric. In this case the mean and variance of log consumption equals to:[64]

$$\mathrm{E}(\log(C_{it})) = \left(1 + \frac{1}{1+\theta}(N-1)\right)\mu \tag{C.13}$$

$$\mathrm{Var}(\log(C_{it})) = \frac{\theta^2 + \frac{1}{N}}{(1+\theta)^2}\sigma^2. \tag{C.14}$$

Comparing Equation C.14 and C.11, we show that openness to trade reduces the country's volatility (consistent with Caselli et al. 2020).

In this case, the certainty equivalent welfare equals to:

$$C_{CE} = \left(1 + \frac{1}{1+\theta}(N-1)\right)\mu + \frac{1}{2}\frac{\theta^2 + \frac{1}{N}}{(1+\theta)^2}\sigma^2(1-\gamma). \tag{C.15}$$

Therefore, if countries are symmetric, openness to trade unambiguously increase a country's welfare.

In contrast, if risk exposures between countries are different, a low-risk country trading with a high-risk country may introduce significant risk to its economy. If these risks are large enough, they are able to offset the increase in expected consumption and lead to lower certainty equivalent welfare for the low-risk country.

3. **Frictionless trade with international risk sharing:** With international risk sharing, the complete international asset market allows countries to equate marginal utility

[64] Log linearize Equation C.12 around the means of L_i's, we get: $\log(\hat{C}_{it}) = \frac{\theta}{1+\theta}\log(\hat{L}_{it}) + \frac{1}{1+\theta}\sum_{i=1}^{N} s_i \log(\hat{L}_{it})$ (where $s_i = \frac{E(L_{it})}{\sum_{i=1}^{N} E(L_{it})} = \frac{1}{N}$), with which we compute the variance.

of consumption:

$$\frac{U'(C_{it})}{U'(C_{jt})} = \frac{\omega_j}{\omega_i}, \tag{C.16}$$

where ω_i denotes a country's Pareto weight. With symmetric countries, these weights equalize across countries, which means that countries should equalize consumption: $C_{it} = C_{jt} \equiv C_t, \forall i, j$.

With international risk sharing, countries that receive a bad shock will borrow from other countries and run a trade deficit. Countries that receive a good shock will lend to other countries and run a trade surplus. The complete international asset market will hedge all such risks. Countries will equalize their marginal utility of consumption to the price of the state contingent claims. Hence, their marginal utility is equalized across countries.

Since markets clear for the state contingent claims, the global resource constraint equals the following:

$$NP_tC_t = \sum_{i=1}^{N} w_{it}L_{it}. \tag{C.17}$$

To solve for consumption, again we plug the formula for the trade flow, Equation C.6, into the market clearing condition for goods, Equation C.9:

$$w_{it}L_{it} = \frac{(w_{it})^{-\theta}}{P_t^{-\theta}} \sum_{j=1}^{N} w_{jt}L_{jt} = \frac{(w_{it})^{-\theta}}{P_t^{-\theta}} NP_tC_t \tag{C.18}$$

This shows that:

$$w_{it} = (L_{it})^{-\frac{1}{1+\theta}} P_t (NC_t)^{\frac{1}{1+\theta}}$$

Plug this into Equation C.19, we get:

$$C_{it} = \frac{1}{N}\left(\sum_{i=1}^{N}(L_{it})^{\frac{\theta}{1+\theta}}\right)^{\frac{\theta+1}{\theta}}. \tag{C.19}$$

Compared with Equation C.12, international risk sharing exposes countries to even more foreign shocks. In Equation C.12, the domestic shock accounts for a greater share in consumption, whereas in Equation C.19, all countries' shocks have equal weights.

Consider symmetric countries. Again, since there is no close form for the mean and variance of C_{it} in Equation C.19, we use a first order approximation. In this case the mean and variance of log consumption equals to:[65]

$$\mathrm{E}(\log(C_{it})) = N^{\frac{1}{\theta}}\mu \tag{C.20}$$

$$\mathrm{Var}(\log(C_{it})) = \frac{1}{N}\sigma^2. \tag{C.21}$$

Since $N^{\frac{1}{\theta}}$ in Equation C.20 is higher than $1 + \frac{1}{1+\theta}(N-1)$ in Equation C.13, international risk sharing increases the mean consumption. It is because risk sharing allows countries to import more when they are hit by bad shocks, which results in welfare gains from trade due to the love of variety, which is not possible when trade must balance.

If $(N-1)\theta > 2$, $\frac{1}{N}$ in Equation C.21 will be smaller than $\frac{\theta^2+\frac{1}{N}}{(1+\theta)^2}$ in Equation C.14. The risk exposure of countries will be reduced by sharing international risks if there are many countries in the world to diversify risks and the international bundle is less important when there is no international risk sharing (if domestic and international bundles are more substitutable). This inequality unambiguously holds with $\theta \geq 2$.

In this case, the certainty equivalent welfare equals to:

$$C_{CE} = N^{\frac{1}{\theta}}\mu + \frac{1}{2}\frac{1}{N}\sigma^2(1-\gamma). \tag{C.22}$$

As long as $(N-1)\theta > 2$, international risk sharing increases welfare unambiguously when compared with (1) trade autarky or (2) frictionless trade but without international risk sharing.

If countries are exposed to different risks, and when a low-risk country trades with a high-risk country in both goods and asset markets, its economy may be exposed to significant risk, since the foreign country now has an even greater share of domestic consumption. When these risks are large enough, they may offset the increase in expected consumption, resulting in lower certainty equivalent welfare for the low-risk country.

[65] Log linearize Equation C.19 around the means of L_i's, we get: $\log(\hat{C}_{it}) = \sum_{i=1}^{N} s_i \log(\hat{L}_{it})$ (where $s_i = \frac{E(L_{it})}{\sum_{i=1}^{N} E(L_{it})} = \frac{1}{N}$), with which we compute the variance.

D Appendix for Stock Market Analysis

D.1 Additional Tables

Table D.1: Concordance between Datastream Sectors and Aggregate Sectors

Datastream sectors	Datastream sector names	Aggregate sectors
MRKTS	Aggreate market	MRKTS
AUPRT	Automobile and parts	AUTMB
BANKS	Banks	FINSV
BMATR	Basic materials	BMATR
BRESR	Basic resources	BRESR
CHEMS	Commodity 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
INDTR	Industrial transportation	INDTR
INSUR	Insurance	INSUR
LEISG	Leisure goods	HHOLD
MEDIA	Media and communication sector	MEDIA
PERSG	Personal good	HHOLD
REINS	Reinsurance	INSUR
RLEST	Real estate	RLEST
RTAIL	Retail	RTAIL
TECNO	Technology	TECNO
TELCM	Telecommunications	TELCM
TRLES	Travel and leisure	INDTR
UTILS	Utilities	UTILS

Description: This table shows the concordance between Datastream sectors and aggregate sectors. We merge Datastream sectors and WIOD sectors at the aggregate sector level.

Table D.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	INDTR
4	B	BRESR	32	H50	INDTR
5	C10-C12	FDBEV	33	H51	INDTR
6	C13-C15	HHOLD	34	H52	INDTR
7	C16	BRESR	35	H53	INDTR
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: This table shows the concordance between WIOD (Timmer et al., 2015) sectors and aggregate sectors. We merge Datastream sectors and WIOD sectors at the aggregate sector level. The WIOD sectors are based on ISIC Rev. 4 classifications.

Table D.3: **Impact of Climate Disasters on Tradable Sectors in Upstream and Downstream Stock Markets: Clustered on Different Level**

Dependent Variable: Cumulative Abnormal Return												
	Full Sample				Hit Port				Didn't Hit Port			
	Upstream		Downstream		Upstream		Downstream		Upstream		Downstream	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Exposure to Foreign Disaster	123.0	161.3	-153.4	-187.9	400.5	448.6	-1,012**	-1,053**	-133.6	-102.0	-73.47	-91.49
	(165.4)	(153.8)	(193.1)	(196.3)	(371.6)	(344.8)	(433.9)	(449.0)	(173.9)	(198.1)	(230.4)	(240.3)
	[152.1]	[134.1]	[185.7]	[170.7]	[336.5]	[313.8]	[465.4]	[476.8]	[183.2]	[206.9]	[240.7]	[224.2]
Exposure to Foreign Disaster	-321.3**		-262.8		-494.4**		-581.0*		-172.9		-191.8	
$\times TS^s$	(119.2)		(203.5)		(184.8)		(331.7)		(158.7)		(214.4)	
	[127.9]		[198.8]		[174.9]		[267.7]		[159.7]		[218.8]	
Exposure to Foreign Disaster		-550.2***		-376.3		-869.4***		-1,075*		-316.0		-266.8
$\times TD^s$		(178.5)		(251.0)		(275.0)		(553.8)		(380.5)		(238.7)
		[191.7]		[219.1]		[260.6]		[518.6]		[375.9]		[222.7]
Observations	12,795	12,795	12,795	12,795	5,235	5,235	5,235	5,235	7,560	7,560	7,560	7,560
Midstream Cou. FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Downstream Cou. FE	No	No	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes
Upstream Cou. FE	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes	No	No
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean Dep. Var	-0.00918	-0.00918	-0.00758	-0.00758	-0.00959	-0.00959	-0.00899	-0.00899	-0.00890	-0.00890	-0.00661	-0.00661
R^2	0.118	0.118	0.107	0.107	0.104	0.104	0.0949	0.0949	0.125	0.125	0.114	0.114

Description: This table presents the estimated parameters of model 11. TS^s is a dummy variable that equals 1 if the sector belongs to basic material, industrial production, or consumer goods sectors. TD^s equals sector s' total trade divided by the sector's total GDP on the world level. The sample is composed of main trade partners of the countries hit by a large climate disaster. We pool all sectors' estimated cumulative abnormal returns to investigate the heterogeneity across sectors. We measure the cumulative abnormal returns with their values at 80 trading days after the beginning of the climate disaster. Robust standard errors in parentheses are two-way clustered at disaster-hit country and stock market country level. Robust standard errors in brackets are clustered at disaster-hit country level. Robust standards error in brackets are clustered at disaster-hit country level. *** p<0.01, ** p<0.05, * p<0.1.

Table D.4: **Impact of Country Institutional Factors on Cumulative Abnormal Returns due to Climate Disasters in Foreign Countries**

Dependent Variable: Cumulative Abnormal Return of the Market								
	Downstream CAR				Upstream CAR			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Exposure to Foreign Disaster	-487.2***	-442.3***	-481.0***	-231.3*	-114.8	-17.30	-363.2***	-96.79
	(153.5)	(156.4)	(157.8)	(125.2)	(111.0)	(174.0)	(120.6)	(128.4)
Home Country: Financial Integration	0.000642				0.000365			
	(0.000432)				(0.000456)			
Exposure to Foreign Disaster	104.1*				72.67			
× Home Country: Financial Integration	(55.67)				(44.56)			
Exposure to Foreign Disaster		352.5				2.844		
× Home Country: Emerging Market		(254.8)				(206.7)		
Foreign Country: Financial Integration			0.00337**				-0.00137	
			(0.00141)				(0.00171)	
Exposure to Foreign Disaster			35.79*				65.08***	
× Foreign Country: Financial Integration			(20.08)				(14.51)	
Exposure to Foreign Disaster				-1,620***				168.2
× Foreign Country: Emerging Market				(520.7)				(182.9)
Observations	12,795	12,795	12,795	12,795	12,795	12,795	12,795	12,795
Midstream Cou. FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Downsteam Cou. FE	Yes	Yes	Yes	Yes	No	No	No	No
Upsteam Cou. FE	No	No	No	No	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean Dep. Var	-0.00758	-0.00758	-0.00758	-0.00758	-0.00918	-0.00918	-0.00918	-0.00918
R^2	0.107	0.107	0.107	0.107	0.118	0.118	0.118	0.118

Description: This table shows the associations between country institutional factors and trading day 80's (from 80 trading days before the disaster to 80 trading days after the disaster) cumulative abnormal return from a foreign climate disaster in the financial sector. The institutional factors include financial integration (the total value of assets and liabilities divided by GDP) and whether the country is an emerging market. Standard errors are presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table D.5: **Association between Exposure to Foreign Climate Risks and Home-country P/E Ratio: Results from Panel Regression**

VARIABLES	(1) Up pooled	(2) Down pooled	(3) Up Interaction	(4) Down interaction	(5) Up placebo	(6) Down placebo	(7) Up placebo interaction	(8) Down placebo interaction
Exposure to Foreign Climate Risk	-24.36**	-28.04*	23.35**	33.25**	39.20***	43.23***	0.654	3.144
	(9.999)	(14.40)	(10.16)	(13.58)	(6.903)	(7.984)	(5.382)	(5.647)
Exposure to Foreign Climate Risk			-126.4***	-161.4***			99.62***	103.4***
× Tradability			(34.23)	(40.80)			(21.92)	(24.26)
Observations	25,041	25,041	25,041	25,041	25,041	25,041	25,041	25,041
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean Dep. Var	-43.83	-43.83	-43.83	-43.83	-43.83	-43.83	-43.83	-43.83
R^2	394.8	394.8	394.7	394.7	394.6	394.6	394.4	394.4
Δ_{sd}	-0.00829	-0.00811	-0.00119	-0.000299	0.0238	0.0252	0.00127	0.00270
Δ_{interq}	-1.196	-1.375	-0.172	-0.0507	5.165	6.439	0.276	0.689

Description: This table shows the association between home-country residual P/E ratio and upstream and downstream exposures to foreign climate risks. Columns 1 and 2 show the impact of upstream and downstream foreign climate risk exposures for all sectors. Columns 3 and 4 add to Columns 1 and 2, respectively, the interaction between upstream and downstream foreign climate risk exposures and the importing and exporting tradability. Columns 5 and 6 present the result with placebo upstream and downstream foreign exposures–openness to trade. Columns 7 and 8 add the interaction between openness to trade and importing and exporting tradability. In Columns 1-2 and 5-6, Δ_{sd} refers to the change in the standard error of the dependent variable associated with one standard deviation increase in the independent variable, Δ_{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 3-4 and 7-8, Δ_{sd} refers to the change in the standard error of the dependent variable associated with one standard deviation increase in the exposure to foreign climate risks for sectors with median readability, Δ_{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. Robust Standard errors in parentheses are clustered at the year level. *** p<0.01, ** p<0.05, * p<0.1.

Table D.6: **Associations between Exposure to Foreign Climate Disasters and Home-country P/E Ratios with Country Fixed Effect**

VARIABLES	(1) Up interaction	(2) Down interaction	(3) Up placebo interaction	(4) Down placebo interaction
Exposure to Foreign Climate Risk	-360.2***	-383.2***	54.68	73.20
× Tradability	(107.6)	(119.6)	(76.48)	(90.46)
Observations	1,235	1,235	1,235	1,235
Country FE	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes
Mean Dep. Var	-43.83	-43.83	-43.83	-43.83
R^2	374.9	375	375.4	375.4

Description: This table shows the association between home-country residual P/E ratio and Sectoral Tradability. Robust Standard errors are presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table D.7: **Associations between Placebo Exposures to Foreign Countries and Home-country P/E Ratios**

VARIABLES	(1) Up GDP	(2) Up GDP per capita	(3) Up GDP growth	(4) Up per capita GDP growth	(5) Up GDP interaction	(6) Up GDP per capita interaction	(7) Up GDP growth interaction	(8) Up GDP per capita growth interaction
Exposure to Foreign Climate Risk	0.691	2.076	346.1	463.4	-0.222	-0.614	-88.00	-115.8
	(1.196)	(3.255)	(428.2)	(464.3)	(0.293)	(0.807)	(110.6)	(118.0)
Exposure to Foreign Climate Risk					2.067	6.104	997.3	1,340
× Tradability					(2.887)	(7.947)	(1,101)	(1,220)
Observations	1,235	1,235	1,235	1,235	1,235	1,235	1,235	1,235
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean Dep. Var	0.00498	0.00498	0.00498	0.00498	0.00498	0.00498	0.00498	0.00498
R^2	375.5	375.5	375.5	375.4	375.6	375.6	375.5	375.5
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
VARIABLES	Down GDP	Down GDP per capita	Down GDP growth	Down per capita GDP growth	Down GDP interaction	Down GDP per capita interaction	Down GDP growth interaction	Down GDP per capita growth interaction
Exposure to Foreign Climate Risk	0.793	2.351	412.8	509.9	-0.382**	-1.051**	-145.4*	-170.8*
	(1.418)	(3.794)	(481.0)	(517.8)	(0.171)	(0.479)	(72.89)	(86.32)
Exposure to Foreign Climate Risk					2.661	7.725	1,283	1,574
× Tradability					(3.478)	(9.422)	(1,252)	(1,376)
Observations	1,235	1,235	1,235	1,235	1,235	1,235	1,235	1,235
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean Dep. Var	-43.83	-43.83	-43.83	-43.83	-43.83	-43.83	-43.83	-43.83
R^2	375.5	375.5	375.4	375.4	375.6	375.5	375.4	375.3

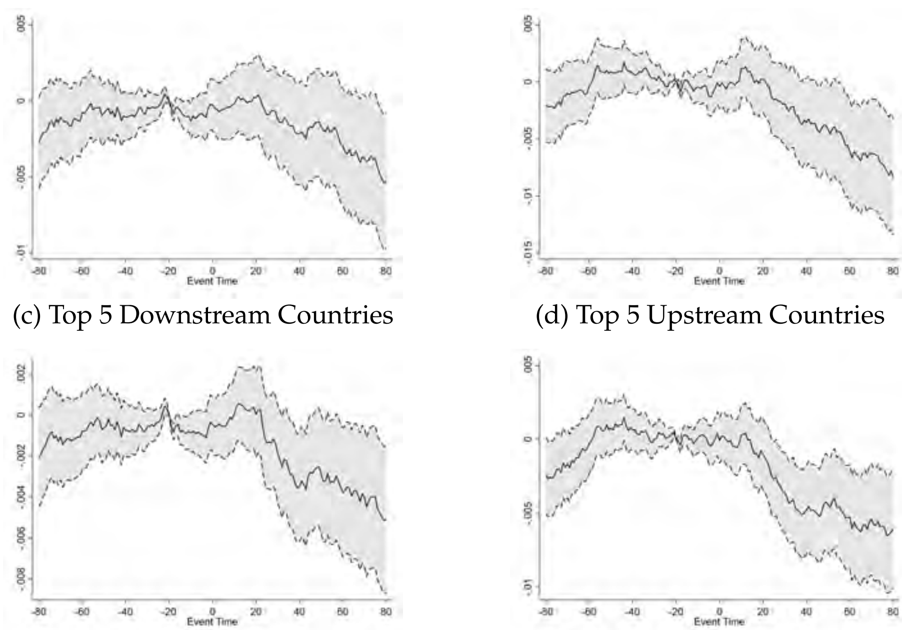
Description: This table shows the association between home-country residual P/E ratio and upstream and downstream placebo exposure measures. Columns 1-4 consider exposures to foreign GDP, GDP per capita, GDP growth, and GDP per capita growth in the upstream countries. Columns 5-8 add interactions with these variables and the respective tradability measures. Columns 9-16 consider the downstream countries. Robust Standard errors are presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

D.2 Additional Figures

Figure D.1: **Impact of Climate Disasters on Top Trade Partners**

(a) Top 3 Downstream Countries (b) Top 3 Upstream Countries

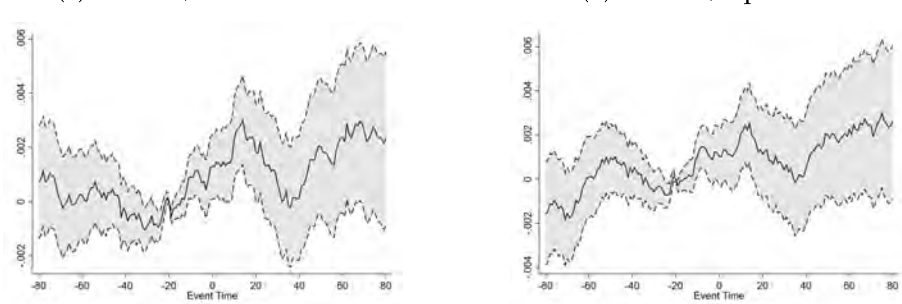
(c) Top 5 Downstream Countries (d) Top 5 Upstream Countries



Description: The figures plot the cumulative abnormal returns in the market indexes of all top 3 and top 5 largest exporting destinations and the top 3 and top 5 largest importing origins of the disaster-hit country from 80 days before the disaster to 80 days after the disaster.

Figure D.2: **Impact of Climate Disasters on Non-major Trade Partners**

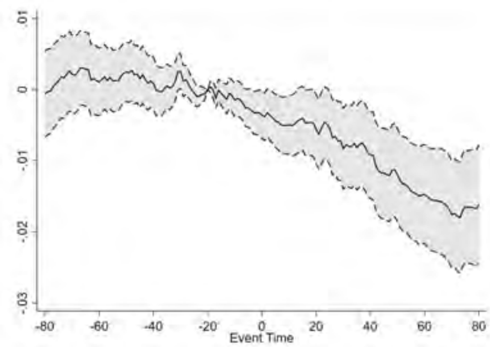
(a) Placebo, Downstream (b) Placebo, Upstream



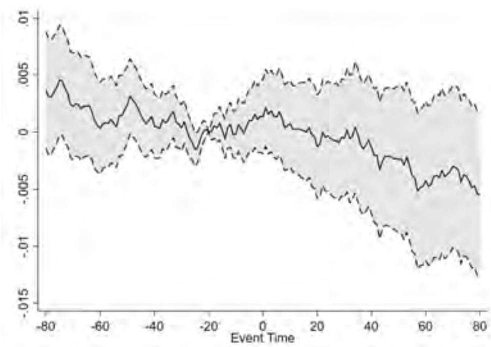
Description: The figures plot the cumulative abnormal returns in the market indexes of the top 10 to 20 largest exporting destinations and the top 10 to 20 largest importing origins of the disaster-hit country from 80 days before the disaster to 80 days after the disaster.

Figure D.3: **Sector-level Stock Market Returns in the Main Downstream Country**

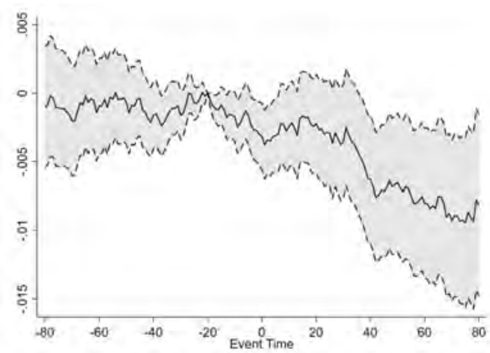
(a) Automobile



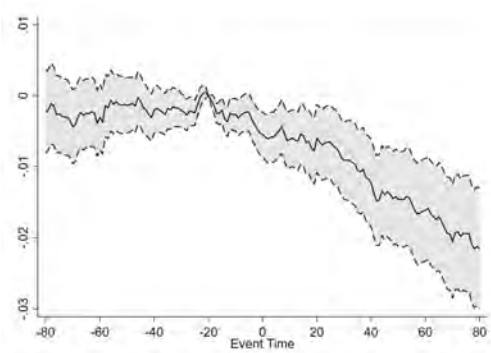
(b) Banks



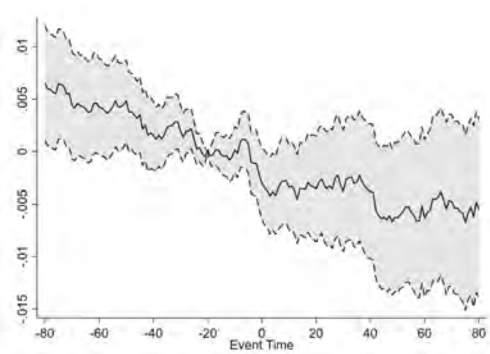
(c) Basic Materials



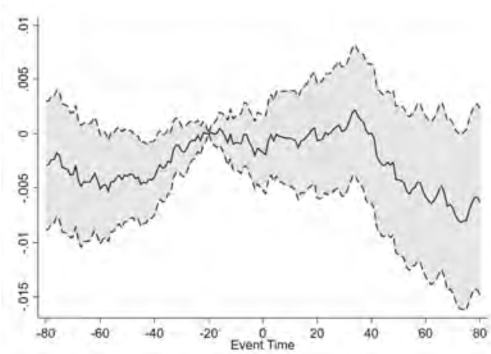
(d) Basic Resources



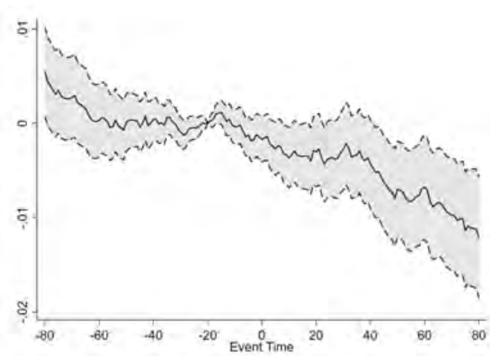
(e) Chemicals



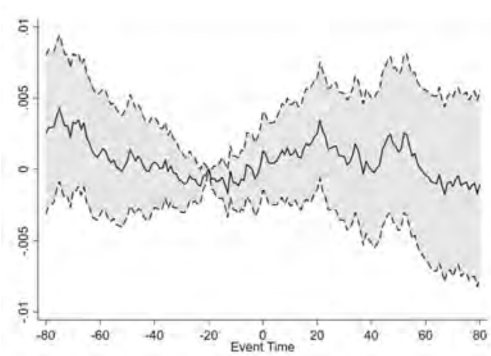
(f) Construction and Materials



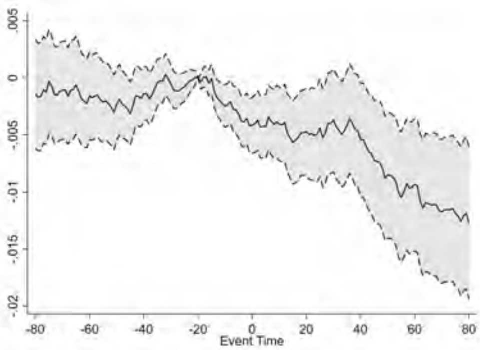
(g) Food and Beverages



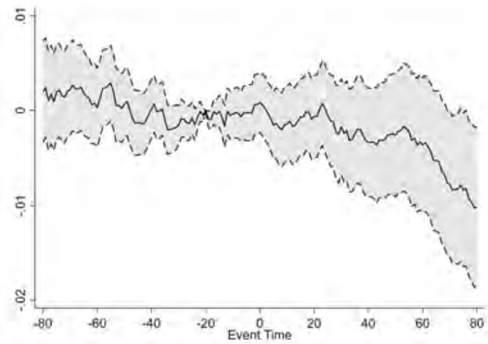
(h) Financial Services



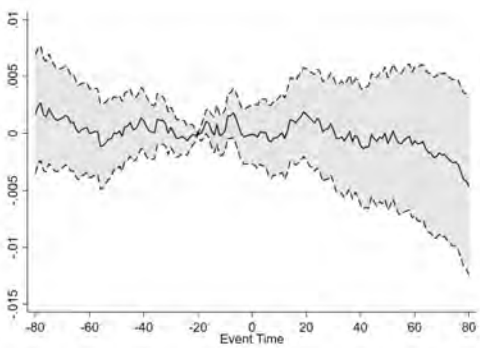
(i) Food Producers



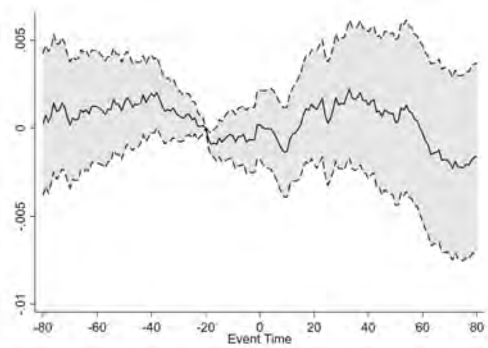
(j) Household Goods and Home Construction



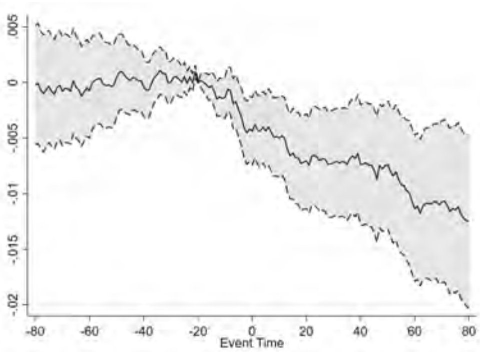
(k) Utilities



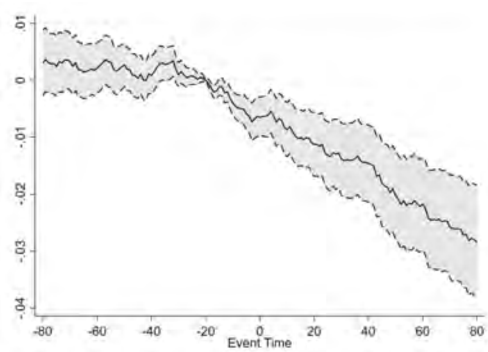
(l) Industrial Goods



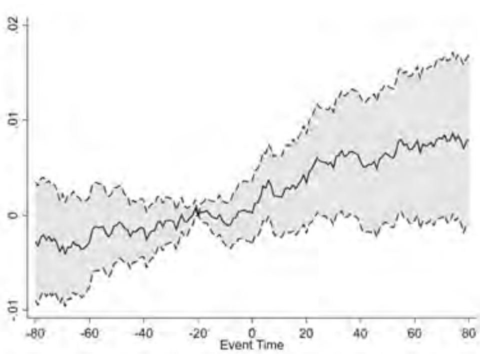
(m) Insurance



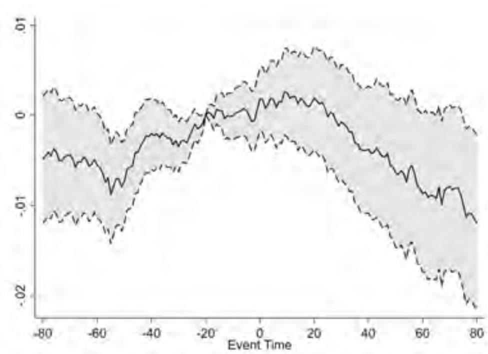
(n) Media and Communication



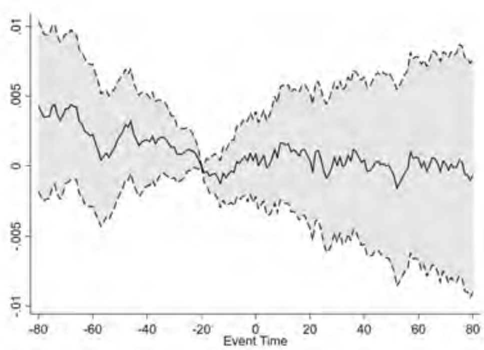
(o) Reinsurance



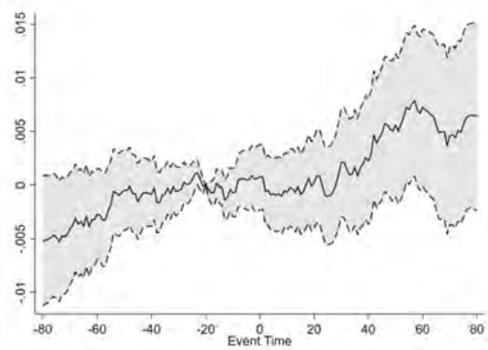
(p) Real Estate



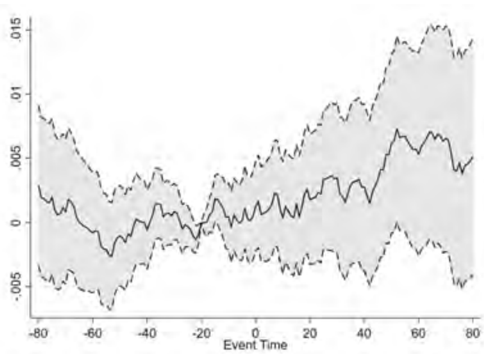
(q) Retail



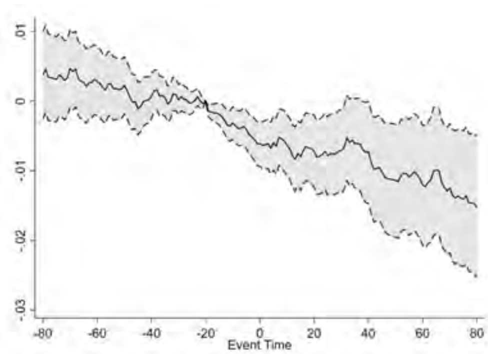
(r) Technology



(s) Telecommunications



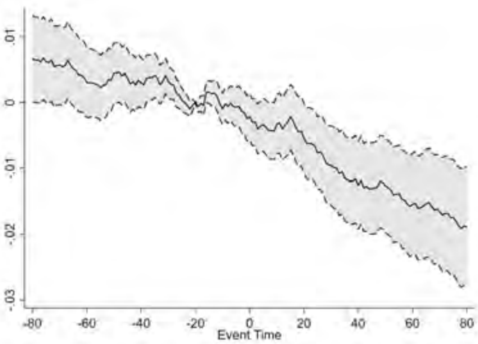
(t) Travel and Leisure



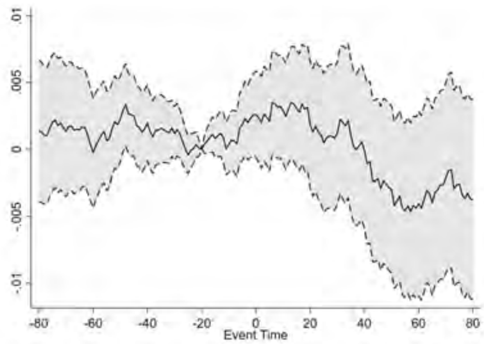
Description: The figures plot cumulative abnormal returns in sector-level stock indexes in the main downstream disaster-hit country from 80 days before the upstream disaster to 80 days after the upstream disaster. The shaded area represents 95 % CI.

Figure D.4: **Sector-level Stock Market Returns in the Main Upstream Country**

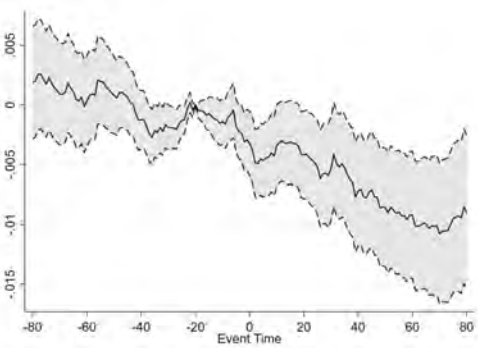
(a) Automobile



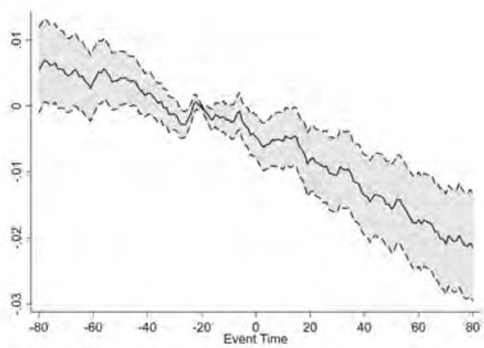
(b) Banks



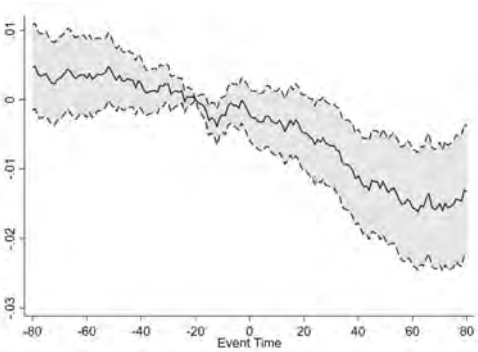
(c) Basic Materials



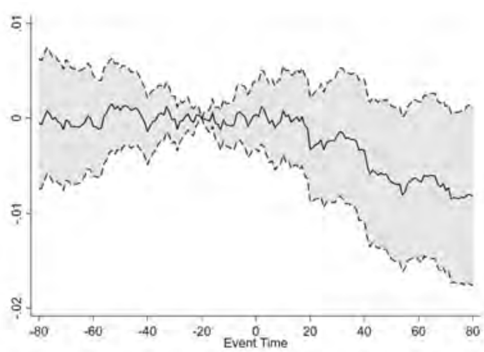
(d) Basic Resources



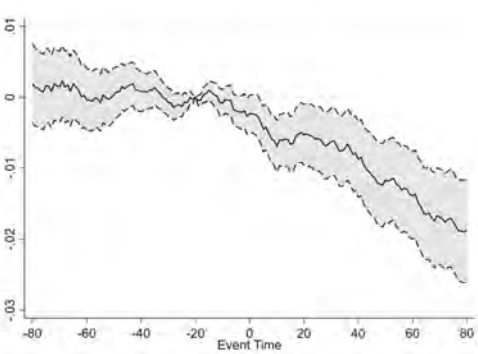
(e) Chemicals



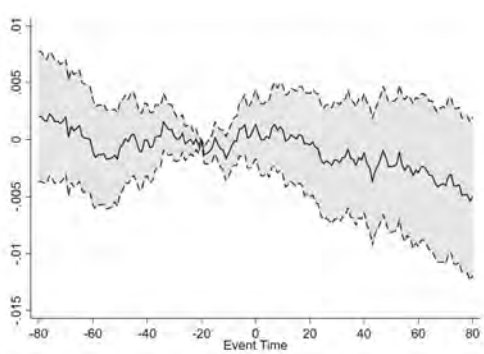
(f) Construction and Materials



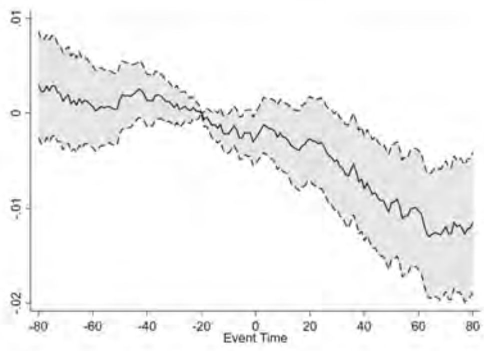
(g) Food and Beverages



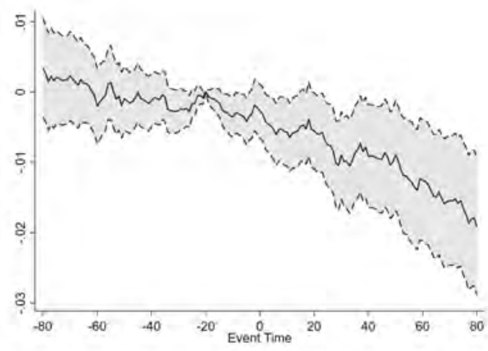
(h) Financial Services



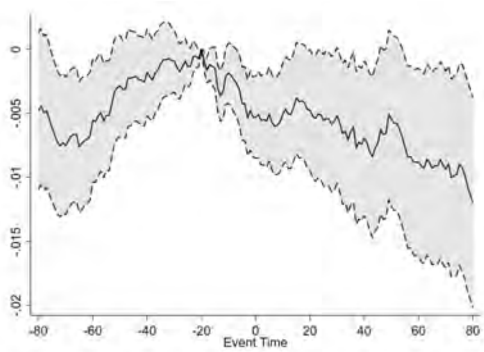
(i) Food Producers



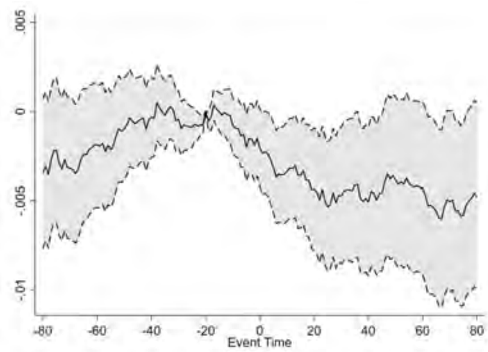
(j) Household Goods and Home Construction



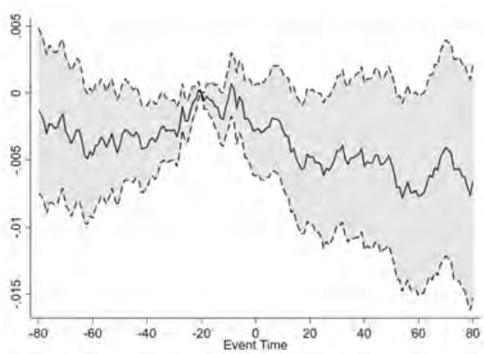
(k) Utilities



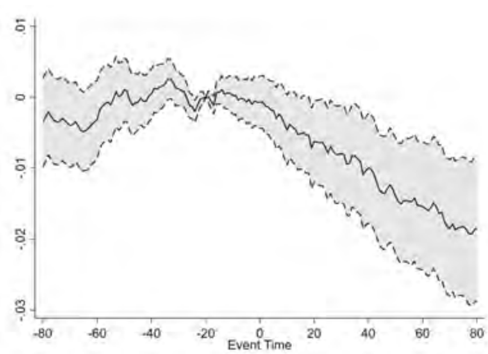
(l) Industrial Goods



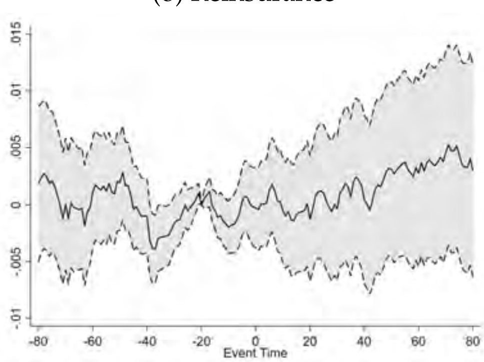
(m) Insurance



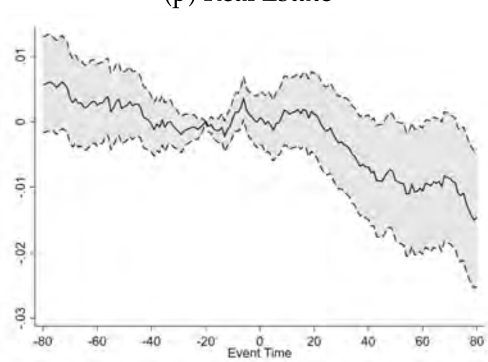
(n) Media and Communication



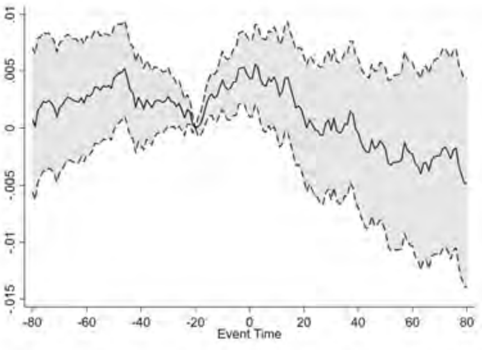
(o) Reinsurance



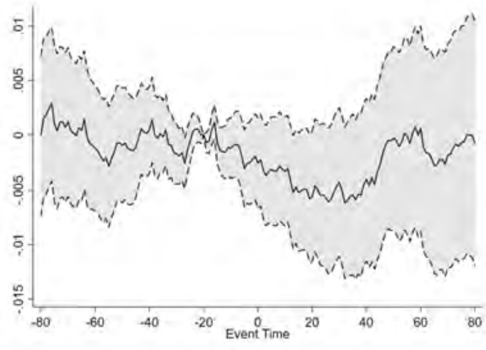
(p) Real Estate



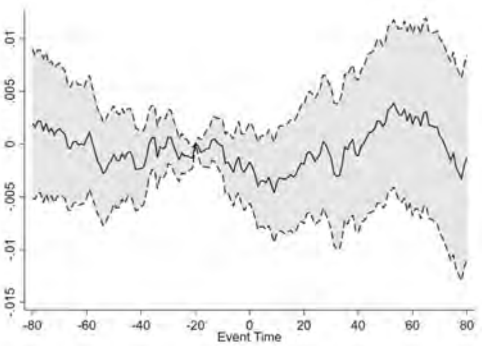
(q) Retail



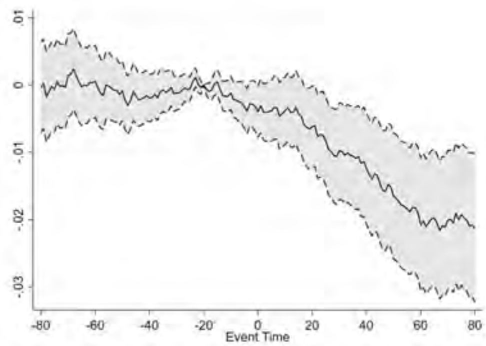
(r) Technology



(s) Telecommunications



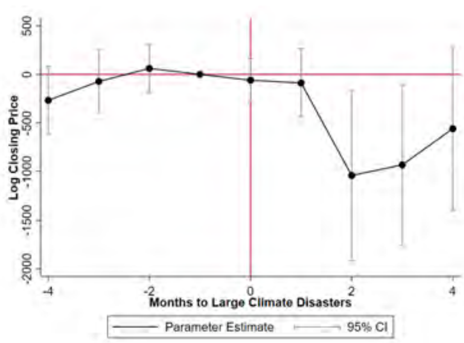
(t) Travel and Leisure



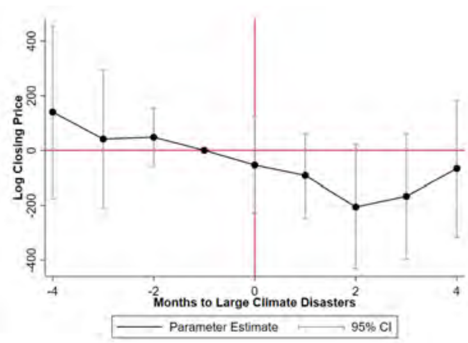
Description: The figures plot cumulative abnormal returns in sector-level stock indexes in the main upstream country from 80 days before the downstream disaster to 80 days after the downstream disaster. The shaded area represents 95 % CI.

Figure D.5: **Impact of Foreign Climate Disasters on Chinese Industrial Firm Stock Prices**

(a) Downstream Chinese Firms



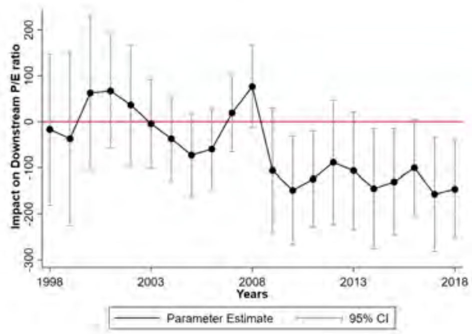
(b) Upstream Chinese Firms



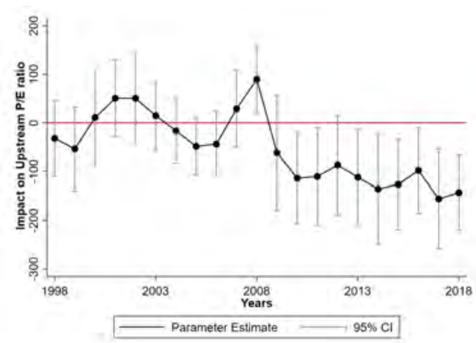
Description: These figures show the impact of climate disasters on the log value of Chinese industrial firms' stock prices at the end of each month. The x-axis contains the number of months to the disaster's starting date. The black curve and vertical segments contain coefficients and 95% CI.

Figure D.6: **Impact of Foreign Climate Risks on Domestic P/E Ratios over the Years**

(a) Downstream P/E Ratios



(b) Upstream P/E Ratios



Description: These figures plot the coefficient b estimated from model 17 and 18 in each year from 1998 to 2018. The black curve and vertical segments contain coefficients and 95% CI.

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