CESifo WORKING PAPERS

8798
2020

Original Version: December 2020
This Version: June 2021

Quantifying the Supply and Demand Effects of Natural Disasters Using Monthly Trade Data

Gabriel Felbermayr, Jasmin Gröschl, Benedikt Heid

Impressum:

CESifo Working Papers
ISSN 2364-1428 (electronic version)
Publisher and distributor: Munich Society for the Promotion of Economic Research - CESifo GmbH
The international platform of Ludwigs-Maximilians University's Center for Economic Studies and the ifo Institute
Poschingerstr. 5, 81679 Munich, Germany
Telephone +49 (0)89 2180-2740, Telefax +49 (0)89 2180-17845, email office@cesifo.de
Editor: Clemens Fuest
https://www.cesifo.org/en/wp
An electronic version of the paper may be downloaded
· from the SSRN website: www.SSRN.com
· from the RePEc website: www.RePEc.org
· from the CESifo website: https://www.cesifo.org/en/wp

CESifo *Working Paper No. 8798*

Quantifying the Supply and Demand Effects of Natural Disasters Using Monthly Trade Data

Abstract

We develop a simple methodology to estimate monthly aggregate supply and demand conditions from bilateral international trade data for about 180 countries and 40 years. We apply our method to measure the short-run effects of natural disasters. In line with theoretical considerations, we find large, persistent negative effects of earthquakes and storms on supply and demand for credit-constrained countries. In other economies, supply is temporarily depressed while demand is temporarily up after a disaster. Using a consistent structural trade model, we back out monthly aggregate productivity measures. We quantify how the adverse productivity effects of the 1992 earthquake in Nicaragua and the 2011 Tohoku earthquake in Japan impacted those countries and their trade partners conditional on different assumptions about trade costs.

JEL-Codes: C680, F140, F180, O470, Q540.

Keywords: economic effects of natural disasters, monthly trade data, dynamic quantitative trade model, earthquakes, storms, aggregate productivity.

Gabriel Felbermayr
IfW Kiel Institute for the World Economy
Kiellinie 66
Germany – 24105 Kiel
gabriel.felbermayr@ifw-kiel.de

Jasmin Gröschl
Ifo Institute – Leibniz Institute for Economic Research at the University of Munich
Germany – 81679 Munich
groeschl@ifo.de

Benedikt Heid
University of Adelaide
School of Economics
5005 SA, Australia
benedikt.heid@adelaide.edu.au

June 24, 2021
We thank participants at the School of Economics Seminar at the University of Utrecht, IPAG Business School in Paris, ETSG 2017 in Florence, ATW 2018 in Auckland, the CESifo Venice Summer Institute 2019 and the CESifo Global Area Conference 2020 for fruitful discussions, useful comments and suggestions. Jasmin Gröschl gratefully acknowledges funding from the German Research Foundation (DFG) under project GR4896/1-1 and the hospitality of the School of Economics at the University of Adelaide during a research visit. Benedikt Heid gratefully acknowledges funding from the Australian Research Council (ARC) under project DP190103524. We thank Saskia Mösle for excellent help with the industrial production data. All remaining errors are our own.

1 Introduction

The Covid-19 pandemic and increasingly frequent natural disasters are making it clear that effective policy responses require timely high-quality data on countries' supply and demand-side conditions. Unfortunately, such information is not available for most poor economies. In this paper, we show how a simple structural trade model can be employed to extract informative proxies from monthly bilateral trade data. Such data have the advantage that they exist for more than 180 countries in a relatively timely fashion. Reaching back to the year 1980, we compile a panel data base of such measures and study the supply and demand side effects of natural disasters domestically and abroad.

Natural disasters affect the livelihood of millions and frequently wreak large economic damage. For example, a recent UN report (UNDRR and CRED, 2020) finds a "staggering rise" in the number of extreme weather events over the past 20 years. To successfully adapt to these events, a clear understanding of their economic consequences is needed. However, while there exists a burgeoning literature on the physical effects of climate change induced natural disasters, the study of the economic consequences of natural disasters is comparably underdeveloped with very mixed results.[1]

One problem may be that aggregate annual GDP, the usual dependent variable in the empirical disasters literature, is too coarse a measure. First, identifying the effects of disasters from aggregate GDP data is difficult because they may have opposing effects on aggregate supply and demand via their productivity and expenditure effects. Second, natural disasters may cause sharp but short-lived disruptions in economic activity that yearly GDP data cannot capture.[2]

To overcome the above mentioned shortcomings, in this paper, we use monthly bilateral trade data to construct proxies for demand and supply side conditions and of aggregate productivity. Trade data have several key advantages. First, unlike measures such as industrial production, monthly data are available for 40 years and for as many as 182 countries including most developing and least developed countries. Second, and quite uniquely, trade data are bilateral in nature. That is, they reflect both the sellers' supply conditions and the buyers' demand conditions at a given point in time, so that they can provide insights on both. Third, bilateral flows are reported twice, once by the exporter and once by the importer, so that random measurement errors

[1] The literature has mostly focused on the long-run economic consequences of disasters by quantifying their effect on annual aggregate economic growth. While some papers find that disasters have long-run growth effects, the evidence is mixed and effects are typically small (Noy, 2009; Loayza et al., 2012; Felbermayr and Gröschl, 2014; Hsiang and Jina, 2014; Dell et al., 2014; Berlemann and Wenzel, 2018). For overviews see Cavallo and Noy (2011) and Auffhammer (2018).

[2] For example, De Mel et al. (2012) report that three months after the December 2004 tsunami, more than 80 percent of Sri Lankan firms had repaired at least part of the damage caused. After hurricane Katrina, Wal-Mart reopened nearly 90 percent of its stores within less than two weeks (Shughart II, 2006). Firms have a profit maximization motive to quickly restore their operations as they can expect to increase their sales as the disaster has literally knocked out part of their competition, see Runyan (2006). Also infrastructure is rebuilt rather quickly: Chang (2000) finds that after the 1995 Kobe earthquake destroyed Kobe's port, container cargo trade recovered two-thirds of its pre-disaster level within six months.

or intentional misreporting are smaller than with alternative short-run measures of economic activity.[3]

To extract separate information on macroeconomic supply and demand conditions from bilateral trade data we make use of a simple extension to a canonical quantitative trade model that gives rise to a gravity equation; see the surveys by Head and Mayer (2014) and Costinot and Rodríguez-Clare (2014) for an overview of these models. We extend the canonical, static model to allow for intertemporal consumption smoothing behavior of consumers via borrowing and lending. In addition, we allow some countries to be credit-constrained.[4] We use the structural model to back out a measure of aggregate productivity from estimated supply-side indicators; the only additional piece of information necessary besides bilateral trade data being yearly GDP.

While not perfect, our monthly activity indicators correlate well with similar measures that are, however, available only for a subset of countries. For example, the overall R^2 in a regression of our supply-side measure on monthly data of industrial production is 0.7. When aggregated to the quarterly level, our productivity measure correlates well with U.S. quarterly measure of TFP for the United States by Fernald (2014). And, at the annual level, it exhibits a good fit to standard measures of annual aggregate productivity such as the TFP series contained in the Penn World Tables by Feenstra et al. (2015).[5]

We use these measures to estimate the short-run economic repercussions of natural disasters and to disentangle their supply-side and demand-side effects. Theory suggests that the response of countries should depend on whether they have access or not to international credit markets. In the event of a disaster, credit constrained countries find it difficult to sustain expenditure by borrowing internationally in order to import while less constrained countries could increase spending to rebuild destroyed assets. Credit constrained countries, thus, may have a hard time to digest the supply shock and to return to pre-disaster levels. In our analysis, we check whether and which type of disaster predominantly affects countries' supply side via its impact on infrastructure and capital stocks, and, ultimately, productivity, or their demand side via effects on aggregate expenditure. Moreover, we can study how long the effects persist. To do so, we measure the

[3]Global nighttime light emission data are available at a monthly level and have been used to study economic conditions, particularly for countries where other data are not available. The majority of the literature uses DMSP (United States Air Force Defense Meteorological Satellite Program) data which are problematic due to measurement errors and unrecorded changes in the measurement techniques which make comparisons across time and space, one of our key concerns, problematic; better VIIRS (Visible Infrared Imaging Radiometer Suite) data are only available since 2012, see Gibson et al. (2021).

[4]Alvarez (2017), Anderson et al. (2020), and Olivero and Yotov (2012) present dynamic multi-country models of bilateral trade flows with capital accumulation with balanced trade within periods, i.e., without borrowing or lending, precluding the possibility of trade imbalances due to consumption smoothing via increasing imports after a shock hits a country. Eaton et al. (2016) present a dynamic multi-country model of bilateral trade with unlimited borrowing or lending, and hence abstract from the heterogeneity in access to finance across countries we are focusing on. Also, to calibrate their model, they rely on detailed sectoral price level data which do not exist at a monthly level for the large set of countries we are considering.

[5]We provide our trade-based monthly supply, demand, and productivity measures for other researchers who may want to apply them to quantify the short-run supply, demand, and productivity effects of other events or policy changes. The measures can be downloaded at `https://benediktheid.weebly.com/`.

intensity of disasters using information provided by the gridded GAME data of geological and meteorological events collected by Felbermayr et al. (2018). These data cover the entire globe at a 0.5 degree grid-cell level from 1980 to 2014.[6]

As our empirical analysis focuses on short-term effects, we concentrate on two short-lived disasters: earthquakes and storms.[7] We group countries into least developed countries and poor countries with high external debt levels, or credit-constrained countries, for short, on the one hand, and non-credit-constrained countries, on the other hand.

We find that that indebtedness and development status play an important role for the adjustment after a disaster strikes. Whereas demand increases in the 12 months after an earthquake hits non-credit-constrained countries, effects are absent or negative for credit-constrained countries. Also, supply contracts much more in credit-constrained countries than in non-credit-constrained countries, exacerbating the effects of disasters. Storms have even larger negative supply effects.

We then apply our framework to individual disaster events, particularly two earthquakes: The 1992 earthquake in Nicaragua, a credit-constrained country, and the 2011 Tohoku earthquake in Japan, a non-credit-constrained country. We find that the 1992 earthquake in Nicaragua lead to an immediate reduction of supply by 37 percent, in addition to a fall in demand by 20 percent in the month of the disaster. These effects remain negative up to 24 months after the earthquake. In Japan, negative supply effects are smaller, with a reduction by 10 percent in the month of the disaster, and turn insignificant after 6 months. Demand shocks turn positive and significant 12 months after the event, and are negligible in the first 6 months.

Finally, using our structural model, we highlight the impact of trade costs on the distribution of spillovers of the disaster effects on other countries: For large high-income countries like Japan, we find spillovers on trading partners, whereas disasters hitting smaller or poorer economies like Nicaragua hardly affect outcomes in other countries. In a counterfactual scenario without trade costs, natural disasters cause less damage in the countries where they occur while trade partners are more strongly affected.

Our results have important policy implications. First, poorer countries are much more vulnerable to natural disasters than richer ones. If weather anomalies increase with climate change, adverse global distributional consequences are to be feared, even if poorer countries are not more frequently hit than richer ones. second, the patterns detected in this paper suggest that credit

[6]The literature often uses disaster data from insurance records. These data have been shown to contain reporting and endogeneity issues. The reporting probability depends on income, losses are unequally distributed across disaster types, less reporting takes place in earlier years, small events are underrepresented, and monetary disaster intensity measures correlate with income per capita (Kahn, 2005; Toya and Skidmore, 2007; Strobl, 2012; Felbermayr and Gröschl, 2014).

[7]Other disasters like prolonged droughts, heat or cold waves may occur for longer periods of time, or are continuous, like climate change. In addition, these longer-term weather or climate changes typically affect agricultural production more than manufacturing and do not destroy trade infrastructure of manufacturing firms' capital stocks in a short amount of time. For the effect of climate change on agricultural trade, see, e.g., Burgess and Donaldson (2010) and Costinot et al. (2016).

constraints increase the damage caused by natural disasters. So, policies meant to help poor countries deal with natural disasters should enable them to gain good access to international financial markets. Ex post debt relief or aid does not suffice. Third, trade integration can act as a de facto insurance against negative shocks such as disasters, but only for large economies, as terms of trade effects cushion the negative effects of reductions in supply caused by disasters. This channel is absent for smaller countries.

Our paper relates to the literature on the short-run economic effects of natural disasters. Strobl (2011) studies how hurricanes impact economic growth in nineteen coastal U.S. states between 1970 and 2005 using quarterly data. Noy (2009) uses a measure of annual disaster intensity that takes into account the month when the disaster occurred; a similar strategy is followed by Melecky and Raddatz (2015), but the outcome variables in both papers are measured at an annual frequency. Noy and Nualsri (2011) use quarterly data to analyze the effect of disasters on government budgets. Cavallo et al. (2014) study the impact of two earthquakes in Chile and Japan on supermarket prices using daily internet price data, whereas Heinen et al. (2018) explore the short-run consumer price effects of natural disasters for a sample of Caribbean countries using monthly price data. Todo et al. (2015), Carvalho et al. (2021), and Boehm et al. (2019) study the disruptive effects of the Tohoku earthquake on supply chains using detailed Japanese firm data. Barrot and Sauvagnat (2016) investigate whether firm-level shocks propagate in production networks considering major natural disasters in the past 30 years in the United States. We contribute to this literature by providing the first estimates of the monthly effects of disasters using trade data for a large set of countries and by quantifying the international spillover effects of these disasters using a dynamic quantitative trade model.

There are a few papers who study the effects of natural disasters on bilateral trade flows using annual data, see, e.g., Gassebner et al. (2010) and Oh and Reuveny (2010). Also, Felbermayr and Gröschl (2013) show that large disasters increase imports of an affected country. These papers provide support for the smoothing hypothesis but say nothing on the effect of disasters on demand, supply, or welfare.

We are not the first to use trade data to uncover productivity levels of countries. Eaton and Kortum (2002) use a similar method to ours to estimate the productivity of countries and, as we do, Costinot et al. (2012) deploy exporter fixed effects to measure the export capacity of an economy. However, these papers use trade data for a single year, and they do not empirically explain cross-sectional or time-series variance in the obtained productivity proxies.

The remainder of the paper is structured as follows. Section 2 presents a simple quantitative trade model which guides our empirical strategy. Section 3 describes the data we use. Section 4 shows how we can identify supply and demand parameters from international trade data. Section 5 illustrates how we can use these parameters to obtain monthly estimates of countries' aggregate productivity. Section 6 applies our framework to identify the supply and demand effects of disasters. Section 7 exploits our structural general equilibrium model to quantify the spillover effects of these disasters on other countries and how these are shaped by the level of trade costs. Section 8 concludes.

2 Conceptual Foundations

We extend a canonical static gravity model of trade flows (see, e.g., Head and Mayer, 2014 and Costinot and Rodríguez-Clare, 2014) to intertemporally optimizing agents and derive an estimable regression equation which allows us to uncover the demand and supply effects of disasters from bilateral trade data.

The representative consumer's life-time utility in country j is given by

$$U_{j,t} = \sum_{t=0}^{\infty} \rho^t u_{j,t} \text{ where } u_{j,t} = \left(\sum_{i=1}^{N} q_{ij,t}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}. \tag{1}$$

Countries are indexed $i, j \in \{1, 2, \ldots N\}$, and t denotes periods. Per period utility $u_{j,t}$ is derived from consuming varieties which are differentiated by origin country as in Armington (1969), where $q_{ij,t}$ is the amount of goods from country i country j consumes. $\rho \in (0, 1)$ denotes the discount rate. The consumer maximizes life-time utility $U_{j,t}$ subject to her budget constraint:

$$\begin{aligned} &\underbrace{p_{ji,t}s_{ji,t}}_{(I)} + \mathcal{I}(j \text{ can borrow}) \left(\underbrace{\sum_{\tilde{t}=1}^{\infty} \left(\frac{1}{1+r} \right)^{\tilde{t}} \sum_{i=1}^{N} p_{ji,\tilde{t}}s_{ji,\tilde{t}}}_{(II)} + \underbrace{(1+r)B_{j,t}}_{(III)} \right) = \\ &\qquad \underbrace{p_{ij,t}q_{ij,t}}_{(IV)} + \mathcal{I}(j \text{ can borrow}) \left(\underbrace{\sum_{\tilde{t}=1}^{\infty} \left(\frac{1}{1+r} \right)^{\tilde{t}} \sum_{i=1}^{N} p_{ij,\tilde{t}}q_{ij,\tilde{t}}}_{(V)} \right), \end{aligned} \tag{2}$$

where the left hand side of Equation (2) is the net present value of country j's sales, and its right hand side the net present value of its expenditure. The ability to borrow on international markets is a fundamental difference between countries in the face of a disaster. Small, poor, and heavily indebted countries are particularly vulnerable to the impact of disasters. Financing disaster recovery by foreign debt is more complicated to obtain with already high levels of external debt; this fact may be exacerbated by a deteriorating trade balance. If a country cannot borrow against future output because they are shut out from international financial markets, a shock to its export capacity directly impacts its import demand, as it cannot engage in consumption smoothing. We make this distinction explicit in our model by the indicator function $\mathcal{I}(j \text{ can borrow})$. (I) is the value of country j's current period sales of quantity $s_{ij,t}$ at price $p_{ij,t}$, (II) is the net present value of all its future sales, and (III) is the value of its net foreign assets, i.e., how much it has borrowed to the rest of the world. (IV) is the value of j' total current period expenditure, and (V) the net present value of all its future expenditure. If a country cannot borrow, the budget constraint collapses to the standard per period budget constraint in a static trade model.

How the ability to borrow affects countries' expenditure in the wake of a disaster can be illustrated by considering two extreme cases: i) A non-credit-constrained country which can borrow on international financial markets, $\mathcal{I}(j \text{ can borrow}) = 1$, and ii) a credit-constrained country which cannot, $\mathcal{I}(j \text{ can borrow}) = 0$. The non-credit-constrained economy can optimize its consumption over time, whereas the credit-constrained country is behaving as if it were myopic, as it cannot smooth consumption by borrowing from abroad. Assume that both countries are hit by the same disaster which temporarily reduces the productivity in the country for some periods. This leads to less sales and hence less export income to finance domestic consumption and imports. Consumers in the non-credit-constrained country anticipate that the fall in productivity is temporary and borrow to make up for the shortfall in domestic production by importing more from abroad, by temporarily increasing the country's trade deficit. This allows households to smooth their consumption and spread the income shock across several time periods in the future. When the same disaster strikes the credit-constrained economy, its households cannot smooth their consumption over time as they cannot finance a temporary trade deficit from abroad. Hence the fall in productivity will be borne fully during the periods when productivity is low. In this country, export sales will fall and hence imports will reduce accordingly. We see that the same disaster can have opposite effects on trade flows of countries, depending on their ability to lend abroad. We therefore allow for a differential effect of disasters on imports and exports depending on whether a country can borrow in our empirical specification.

Maximizing Equation (1) subject to (2) reveals that $q_{ij,t} = a_i^{1-\sigma} P_{j,t}^{\sigma-1} p_{ij,t}^{-\sigma} E_{j,t}$, where per period expenditure is given by $E_{j,t} = \sum_{i=1}^{N} p_{ij,t} q_{ij,t}$ and where country j's CES price index in period t is given by $P_{j,t} = \left(\sum_{i=1}^{N} p_{ij,t}^{1-\sigma}\right)^{\frac{1}{1-\sigma}}$. Firms produce varieties under constant returns to scale and perfect competition at unit cost $c_{i,t}$. As evidenced by Boehm et al. (2019), international input linkages between countries are one way how natural disasters spill over across countries. We therefore model firms which produce goods by combining labor and intermediate goods (both domestic and foreign) using a Cobb-Douglas technology according to $p_{i,t} = c_{i,t} = \frac{1}{A_{i,t}} w_{i,t}^{\beta} P_{i,t}^{1-\beta}$, where β is the labor cost share in production, $w_{i,t}$ is the wage paid to a worker in country i in period t and $A_{i,t}$ is the country's total factor productivity. Sales from country i to country j at time t can then be written as

$$X_{ij,t} = \left(\frac{\tau_{ij,t} c_{i,t}}{P_{j,t}}\right)^{1-\sigma} E_{j,t}, \tag{3}$$

where $\tau_{ij,t}$ are iceberg-type trade costs as introduced by Samuelson (1954).

Taking logs of Equation (3), we can write

$$\ln X_{ij,t} = \underbrace{(1-\sigma)\ln(c_{i,t})}_{\mu_{i,t},\ \text{supply}} + \underbrace{\ln\left(\frac{E_{j,t}}{P_{j,t}^{1-\sigma}}\right)}_{\zeta_{j,t},\ \text{demand}} + \underbrace{(1-\sigma)\ln\tau_{ij,t}}_{\text{bilateral trade costs}} . \tag{4}$$

It is worth pointing out that conditional on productivity and the level of dynamically chosen optimal monthly expenditure, our dynamic model is identical to a standard static trade model such as those discussed in Head and Mayer (2014), and Equation (4) is a standard bilateral gravity regression. Hence, we can decompose trade flows into a measure of a country's export capacity or supply, $\mu_{i,t}$, its level of effective demand, $\zeta_{j,t}$, as well as a measure of bilateral trade costs, $(1-\sigma)\ln\tau_{ij,t}$. Disaster shocks can occur either in the exporting country i or the importing country j. The demand and supply effects of disasters are therefore captured by $\mu_{i,t}$ and $\zeta_{j,t}$. Having described our theoretical framework, we turn to bringing it to the data.

3 Data

In this section, we describe the trade data which we use to identify the supply and demand parameters. We also describe the disaster data we use in our application and all other data we use in the remainder of the manuscript.

Trade Flows and Gravity Controls. International trade data on monthly bilateral merchandise trade flows come from the IMF's Direction of Trade Statistics (DoTS). The data capture trade between 182 countries from 1980 to 2019, but the panel is unbalanced.[8] The geographical variables capturing trade costs are from CEPII, see Mayer and Zignago (2011). Information on trade policy variables come from the WTO or from Baier et al. (2014).[9]

Natural Disasters. We use the improved version of the Geological and Meteorological Events (GAME) Database based on Felbermayr and Gröschl (2014) and updated in Felbermayr et al. (2018). It contains physical intensities of natural disasters such as earthquakes, volcanic eruptions, storms, droughts, excessive precipitation and temperature anomalies of $0.5° \times 0.5°$ on a monthly basis from 1979 to 2014 for 232 countries.

As the data combine physical intensities for disasters at the grid level on a monthly basis, we

[8] Besides missing trade data, several new countries enter the sample in the early 1990s due to the end of the Cold War. See Table A1 in the Appendix for summary statistics.

[9] More precisely, we draw data on regional trade agreements from the WTO RTA-Gateway, available at `https://www.wto.org/english/tratop_e/region_e/region_e.htm`. Information on non-reciprocal trade preferences (generalized system of preferences, GSP) are from Jeffrey Bergstrand's homepage `https://sites.nd.edu/jeffrey-bergstrand/`. We update this information using primary sources from the WTO, available at `http://ptadb.wto.org/ptaList.aspx`.

aggregate physical intensities of earthquakes and storms to the country level by first mapping the 0.5 degree grid cells to the country level. We then calculate a population-weighted arithmetic mean and scale respective disaster variables by population within a grid cell. By this we account for the fact that the impact of a disaster on economic activity depends on whether the affected area is densely or sparsely populated. For disaster effects, it is potentially important whether and how strongly an economic center was hit. Also, countries with a larger surface area have a higher probability of being hit by a disaster. On the other hand, the larger a country, the less likely it is that a disaster striking at a given location has a significant impact on the country's overall economy or trade. Using the mean of population-weighted intensity measures over country grid-cells takes into account these concerns.

(a) Earthquakes. We measure earthquakes by their physical magnitude from the Incorporated Research Institutions for Seismology.[10] An earthquake is defined to occur within a country when part of the country lies within 50 km of its epicenter. The raw data contain a large amount of earthquakes below the magnitude of 2.5. According to UPSeis[11], seismographs register these earthquakes, but these events are hardly felt. It is generally assumed that these low-intensity earthquakes do not cause any damage or disruption and we thus set them to zero. The resulting maximum earthquake magnitude is distributed between 0 and 9.2. In our baseline regression, we translate earthquake intensities into treatment dummies taking the value one if an earthquake has a intensity of an UPSeis earthquake magnitude class 2 (moderate) or higher, i.e., a magnitude of five or higher, and zero otherwise.[12]

(b) Storms. We combine two data sources for our storms measure: (i) Hurricane wind speeds in knots for locations and paths of hurricane centers come from the International Best Track Archive for Climate Stewardship (IBTrACS) v03r07, provided by the World Meteorological Organization (WMO) and the US National Oceanic and Atmospheric Administration (NOAA). Hurricanes are mapped using a wind field model provided by Geiger et al. (2018). (ii) Wind speeds of winter and summer storms in knots come from the Global Summary of the Day (GSOD) statistics. Weather station data are used as complements to IBTrACS. To obtain wind speeds for all grid cells and respective countries, we rely on Felbermayr et al. (2018) who provide kriged wind speed data. Putting the hurricane windfield data on top of the kriged weather station data results in a combined grid-population-weighted wind speed of 5.9 up to 126.8 knots. In our baseline regression, we translate disaster intensities into treatment dummies taking the value one

[10] IRIS provides earthquakes by different magnitudes (e.g., Richter Scale, body wave, surface wave, moment magnitude). All follow a logarithmic scale, are valid in their respective range, and can be compared with each other. Moment magnitude is preferred over other scales if available for the respective event as it is the most uniformly applicable and most reliable magnitude scale.

[11] UPSeis is a program and educational site created by the Michigan Technological University for budding seismologists and to teach the general public about seismology. Earthquake magnitude scales can be found at UPseis, see `http://www.geo.mtu.edu/UPSeis/magnitude.html`.

[12] For a definition of earthquake magnitude classes see `http://www.geo.mtu.edu/UPSeis/magnitude.html`. Earthquakes are classified in categories ranging from minor to great, depending on their magnitude, their damage effects, and the estimated frequency happening each year.

if a storm has a higher intensity than the Saffir-Simpson hurricane wind scale of 65 kt (category 1 or higher), and zero otherwise.Summary statistics of our disaster variables can be found in Table A1 in the Appendix.

Credit-Constrained Countries. As the empirical counterpart to $\mathcal{I}(j$ can borrow), i.e., to classify countries as credit-constrained countries, we combine information from the United Nations and the World Bank. We group countries into two groups: credit-constrained countries (CCCs) and non-credit-constrained countries (non-CCCs). We define credit-constrained countries as the 70 least developed countries (LDCs), heavily indebted poor countries (HIPCs) and landlocked developing countries (LLDCs) in our sample, and the remaining 112 countries as non-credit-constrained. For the definition of LDCs and LLDCs, we follow the United Nations' list of membership and graduations.[13] The classification on HIPCs stems from the World Bank.[14] Countries in these three groups partially overlap. LDCs comprise 47 countries, and HIPCs include 39 developing countries—33 of which are in Africa—with high levels of poverty and unmanageable or unsustainable debt burdens. See Tables A2 and A3 in the Appendix for a detailed country list.

GDP per Capita. To estimate model-consistent productivity parameters for our counterfactual simulations, we use GDP per capita in current US$ (`NY.GDP.PCAP.CD`) from the World Development Indicators as a proxy for a countries' unit production costs. The data is available for 1980 to 2019.

Data for Validation Exercises. To validate our estimates, we use data on total factor productivity and industrial production from three sources. We use annual TFP data (variable `ctfp`) from the Penn World Tables (PWT) 10.0 by Feenstra et al. (2015), available at `www.ggdc.net/pwt`. We use quarterly data on TFP for the U.S. by Fernald (2014).[15]
For monthly industrial production, index data are available from the IMF's International Financial Statistics for 65 countries, a subset of the countries in our sample.[16]

[13]The current list of LDCs and the timeline of countries' graduation are available at `https://www.un.org/development/desa/dpad/least-developed-country-category/ldc-graduation.html`. A list of LLDCs is available at `https://unctad.org/topic/vulnerable-economies/landlocked-developing-countries/list-of-LLDCs`.

[14]See `https://www.worldbank.org/en/topic/debt/brief/hipc`.

[15]The updated version `data_quarterly_2020.03.05` contains data until 2019Q4 available at `https://www.johnfernald.net/TFP`.

[16]We use the "Economic Activity, Industrial Production, Index (AIP_IX)" series from January 1980 to December 2019 for all available countries in our dataset. The data can be accessed at `https://data.imf.org/?sk=4c514d48-b6ba-49ed-8ab9-52b0c1a0179b`.

4 Identifying Supply and Demand Parameters from Trade Data

To identify the supply and demand parameters, we estimate Equation (4) in levels using a Poisson Pseudo-Maximum-Likelihood (PPML) estimator. Hence,

$$X_{ij,t} = \exp(\mu_{i,t} + \zeta_{j,t} + \mathbf{x}'_{ij,t}\boldsymbol{\beta} + \varepsilon_{ij,t}), \tag{5}$$

where we have specified the bilateral trade cost term $\tau_{ij,t}$ by a linear combination of observable trade cost drivers typically used in the literature, see Head and Mayer (2014), $\mathbf{x}'_{ij,t}\boldsymbol{\beta}$. $\mu_{i,t}$ and $\zeta_{j,t}$ are exporter×month and importer×month fixed effects which capture the supply and demand side components of Equation (4), including the effects of natural disasters. $\varepsilon_{ij,t}$ is a well-behaved error term.[17] The PPML estimator is the only one consistent with the general equilibrium adding up constraints implied by a trade model such as ours, see Fally (2015). It also takes into account the inherent heteroskedasticity of trade flows, see Santos Silva and Tenreyro (2006). In a second step, we then use the estimated demand and supply parameters μ_{it} and ζ_{jt} to identify the short-run effects of disasters. Two-step approaches have gained prominence in the econometric modeling of trade flows to identify the trade effects of country-specific variables.[18]

Drawing on about 7.6 million observations from 1980-2019 and 181 countries, our Poisson model yields an R^2 of 0.889. The estimated coefficients $\boldsymbol{\beta}$ on the controls contained $\mathbf{x}_{ij,t}$ reveal no surprises. The log of distance is 0.804, the one on the common border dummy 0.541, on the RTA dummy 0.350 and on GSP status 0.024, all estimates being statistically significant at the 1%-level.

While gravity models like Equation (5) are routinely used to quantify trade costs while controlling for supply and demand effects as captured by $\mu_{i,t}$ and $\zeta_{j,t}$, less is known about whether the latter parameters capture salient features of the fluctuations in aggregate demand and supply at the monthly level. We therefore validate our estimated parameters in this section before we proceed to the estimation of the disaster effects. If $\mu_{i,t}$ and $\zeta_{j,t}$ capture salient feature's of the variation in countries' aggregate supply and demand, they should correlate with industrial production. Monthly industrial production index data are available from the IMF's International Financial Statistics for 65 countries, a subset of the countries in our sample. Table 1 regresses the log

[17]In line with most of the gravity literature, Equation (5) does not include a direct measure of applied tariffs, as tariff data are missing for many years and countries. We are confident, however, that tariffs do not bias our estimates in a significant way: First, bilateral reductions in applied tariffs due to regional trade agreements are captured by the RTA dummy and zero tariffs for developing countries due to preferential agreements are captured by the GSP dummy, controlling for the majority of applied tariff reductions observed between countries. Second, in our regression, $\mu_{i,t}$ and $\zeta_{j,t}$ automatically also control for most-favored nation tariffs (MFN) applied by an importing country to all WTO member countries if there is no regional or preferential trade agreement in place. In line with our argument, Heid et al. (2021) find that once controlling for MFN tariffs and RTAs, applied tariff rates do not have a significant effect on bilateral trade. The regressions do not contain pair-specific fixed effects ξ_{ij}. The reason is that, with our unbalanced panel, including ξ_{ij} would jeoparize clean identification of the supply and demand terms $\mu_{i,t}$ and $\zeta_{j,t}$.

[18]See Eaton and Kortum (2002), Redding and Venables (2004), Head and Ries (2008), Head and Mayer (2014), Egger and Nigai (2015), Heid and Larch (2016), and Anderson and Yotov (2016) for recent examples.

Table 1: Predicting Industrial Production by Estimated Supply and Demand Parameters

	(1)	(2)	(3)
Dep. Var.: $\ln(IPIndex_{i,t})$		industrial production	
Supply conditions $\mu_{i,t}$	0.551***		0.336***
	(0.069)		(0.074)
Demand conditions $\zeta_{i,t}$		0.630***	0.294***
		(0.076)	(0.062)
R^2 (overall)	0.70	0.68	0.72
R^2 (within)	0.56	0.53	0.59

Notes: *** denotes significance at the 1% level. All specifications contain country fixed effects. Standard errors are clustered at the country level (in parentheses). Time period: Unbalanced panel from January 1980 to December 2019. N=21049.

industrial production index on the estimated supply and demand parameters and on country fixed effects. The latter are needed to control for the country-specific base years used in the production index data. We see that both supply and demand parameters predict a significant amount of the within variation of industrial production, i.e., excluding the variation explained by the country fixed effects, see columns (1) and (2). Also, while both supply and demand measures are correlated (correlation of 0.90), they have separate explanatory power, as evidenced by their individual significance and the increase in the R^2 in column (3) where we include both measures simultaneously.

In sum, our estimated supply and demand parameters correlate well with observed monthly fluctuations in industrial production, both across countries and across time, validating their use for our analysis.

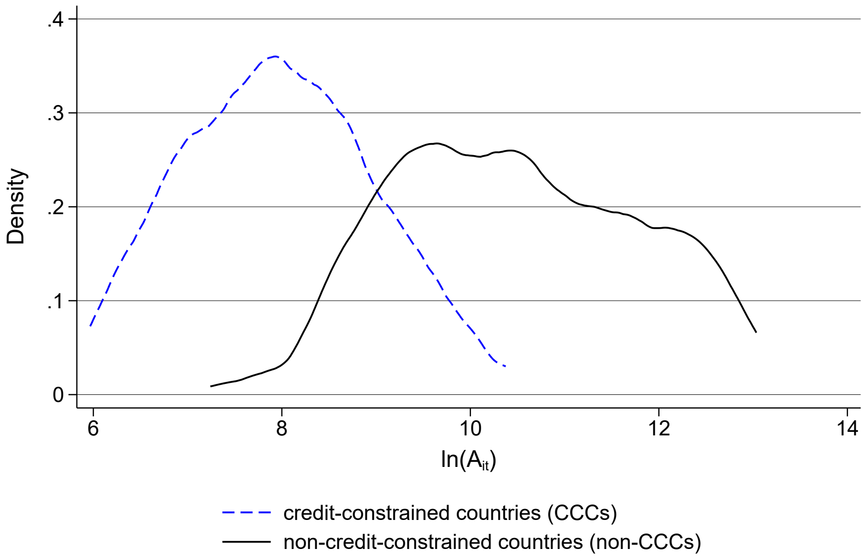
5 Identifying Monthly Productivity from Supply Parameters

We can use our estimates from Section 4 in combination with our model from Section 2 to identify monthly productivity. Particularly, Equation (4) implies a simple way to uncover $A_{i,t}$ from the supply parameters, i.e., the exporter fixed effects $\mu_{i,t}$, from estimating Equation (5):

$$\mu_{i,t} = (1-\sigma)\ln(c_{i,t}) = (1-\sigma)\ln\left(\frac{w_{i,t}^{\beta} P_{i,t}^{1-\beta}}{A_{i,t}}\right). \tag{6}$$

We calculate $A_{i,t}$ from the exporter fixed effect using GDP per capita in year t as a proxy for a country's level of unit production costs, $w_{i,t}^{\beta} P_{i,t}^{1-\beta}$, and assuming $(1-\sigma) = -5.03$, the preferred estimate of Head and Mayer (2014), p. 165, who conduct a meta study on estimates of the

Figure 1: Distribution of Estimated Productivity Parameters



Notes: Figure shows Epanechnikov kernel density plots of estimated monthly productivity parameters, $A_{i,t}$, for December 2019, the last month in our sample, for credit-constrained (bandwith = 0.37) and non-credit-constrained countries (bandwith = 0.45).

elasticity of substitution. We can then solve Equation (6) for $A_{i,t}$:

$$\ln\left(A_{i,t}\right) = \ln\left(w_{i,t}^{\beta} P_{i,t}^{1-\beta}\right) - \frac{\mu_{i,t}}{1-\sigma} = \ln\left(\text{GDP p.c.}\right)_{i,t} + \frac{\mu_{i,t}}{5.03}. \tag{7}$$

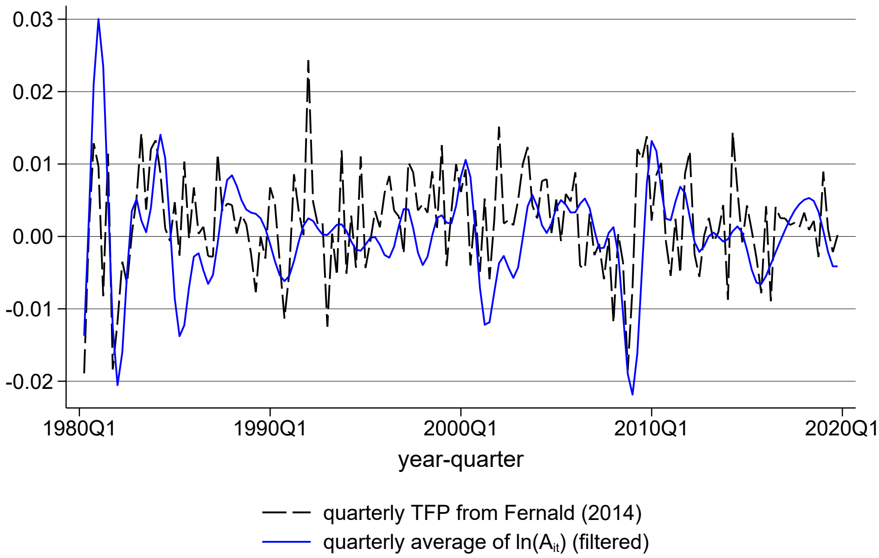
Figure 1 gives a first look at the results. It shows the distribution of the estimated productivity parameters split into two groups of countries, credit-constrained countries and non-credit-constrained countries. Our method identifies intuitively plausible productivity differences between these two groups. The figure also shows that the variance of the productivity parameters is larger for the non-credit-constrained countries, reflecting the fact that this group not only contains high-income countries but also low-income countries with low debt levels.

We would like to compare our productivity measures to other monthly estimates of productivity or total factor productivity (TFP) for a large set of countries. However, monthly productivity measures for a large set of countries do not exist. We therefore compare our monthly estimates to measures at a lower frequency.

Fernald (2014) presents TFP for the U.S. at a quarterly frequency.[19] We therefore calculate the quarterly average of our monthly productivity measures. We follow Fernald (2014) and apply the Christiano and Fitzgerald (2003) band pass filter to filter out cyclical components of less than six and more than 32 quarters (including a drift parameter), following the standard in the

[19]These data are regularly used to evaluate productivity shocks, see, e.g., Eaton et al. (2016) and Ramey (2016).

Figure 2: Comparison with Quarterly TFP Data for the United States

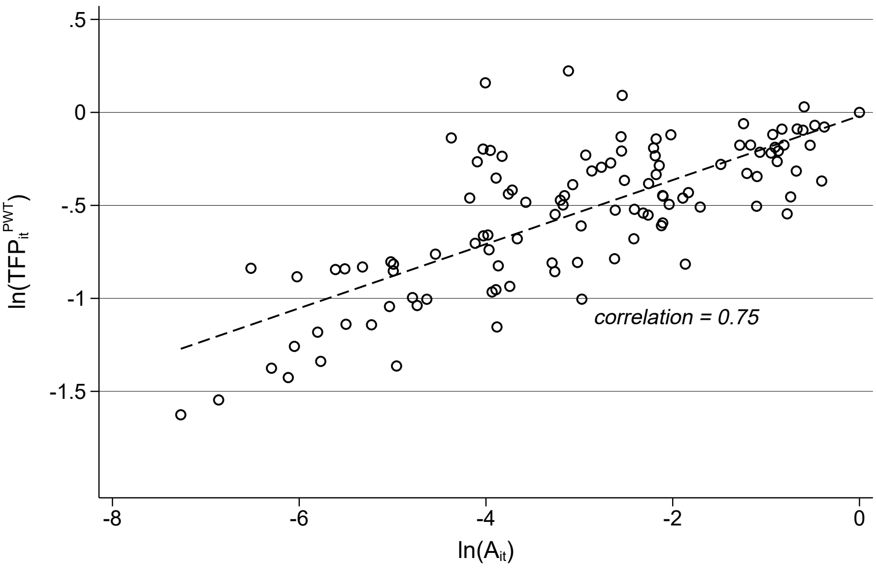


Notes: Figure shows the quarterly TFP measure calculated by Fernald (2014) (and updated until 2019Q4) and our estimated productivity measures for the United States, reported as quarterly changes. For the comparison, we average our monthly estimate for each quarter and apply the Christiano and Fitzgerald (2003) band pass filter, removing cyclical components below six and above 32 quarters, while including a drift parameter.

business cycle literature, see Baxter and King (1999). We present the time series of both our productivity estimates as well as the TFP measure calculated by Fernald (2014) for the U.S. in Figure 2. The correlation between the two time series is 0.36. Hence our method does pick up some part of the variance of the alternative TFP measure typically used in the literature, at least for the U.S. It is not surprising that the correlation is not higher, though. We use trade data, but domestic TFP estimates use measures of domestic output. Economies only trade part of their output, and trade-related productivity shocks need not be perfectly correlated with shocks affecting output destined for domestic consumption. For example, services make up a large part of domestic production.

We now turn to check whether our productivity parameters also capture cross-country differences in productivity. The measure most often used to proxy total factor productivity for a wide range of countries is provided by the Penn World Tables (Feenstra et al., 2015), albeit only at an annual level. We therefore aggregate our productivity measures by calculating the log annual average of A_{it} for each country and compare it to the measure of log total factor productivity at current PPPs. To make measures comparable, we follow Feenstra et al. (2015) and normalize our productivity measures such that $A_{USA,t} = 1$ in all years. To avoid correlation being driven by time series persistence, we show a scatter plot for 2019 only, the last year in our sample, in Figure 3. The correlation between the two measures is 0.75, indicating that our productivity measure derived from our trade gravity estimates is able to capture meaningful variation in productivity differences across countries.

Figure 3: Comparison with Annual TFP Data from the Penn World Tables in 2019



Notes: Figure shows a scatter plot and linear fit of the log annual TFP measure in PPPs (`ctfp`) from the Penn World Tables 10.1 by Feenstra et al. (2015) and the log annual country-average of our estimated productivity measures for a cross-section of 111 countries that appear both in the PWT and our dataset in 2019, the last year of our data. For the comparison, we average our monthly estimate for each year and country and normalize such that $A_{USA,t} = 1$ for every year, as in the Penn World Tables.

Overall, while not perfect, our method picks up productivity differences across countries and across time reasonably well. It can be easily applied to a large sample of countries using only trade data and a measure of GDP per capita. Importantly, it can be constructed at monthly frequency and circumvents the need for detailed data on input use required by other measures of productivity, but which are only available at annual frequency and which involve more complex procedures. Our measure therefore seems to be complementary to existing methods on productivity measurement.

6 Quantifying the Supply and Demand Effects of Disasters

6.1 Regression Specification

We can use our demand and supply parameters to identify the short-run supply and demand effects of disasters. We focus on two types of disasters which are particularly short-lived: earthquakes and storms. To identify their effects, we specify the following regressions:

$$\begin{aligned}\mu_{i,t} &= \sum_{k=0}^{K}\alpha_k\mathcal{I}(i \text{ can borrow})\times D_{i,t-k}+\sum_{k=0}^{K}\alpha_k^*[1-\mathcal{I}(i \text{ can borrow})]\times D_{i,t-k}+\\ &+ \rho_{i,m}+\delta_i f(t)+\eta_t+\varepsilon_{i,t} \end{aligned}\tag{8}$$

$$\begin{aligned}\zeta_{i,t} &= \sum_{k=0}^{K}\beta_k\mathcal{I}(i \text{ can borrow})\times D_{i,t-k}+\sum_{k=0}^{K}\beta_k^*[1-\mathcal{I}(i \text{ can borrow})]\times D_{i,t-k}+\\ &+ \rho_{i,m}+\delta_i f(t)+\eta_t+\varepsilon_{i,t} \end{aligned}\tag{9}$$

where $\mu_{i,t}$ and $\zeta_{i,t}$ are our estimated monthly supply and demand parameters from Equation (5) and $D_{i,t-k}$ are contemporaneous and lagged measures of earthquakes (EQ) and storms (ST). K defines the maximum number of periods an earthquake or storm is allowed to influence monthly exports or imports, respectively. To control for potential anticipation effects, we also include a lead variable. Note that according to Equation (5), $\ln(\exp(\mu_{i,t})) = \mu_{i,t}$ captures the log of the supply side component of the economy. Hence the effect of a storm or earthquake, α_k, can be interpreted as a semi-elasticity, i.e., $\alpha_k \times 100$ is the percentage effect of a storm or earthquake on supply in a non-credit-constrained country, i.e., which can borrow, α_k^* in a credit-constrained-country, i.e., a country that cannot borrow, and similarly for the other estimated parameters.

Import and export data as well as storms exhibit seasonality. These seasons differ across countries: Whereas most hurricanes in the Atlantic occur from June to November, tropical cyclones in the Pacific mostly occur in different months, depending on the respective hemisphere. Consumption and production may also differ due to different seasons in the Northern and Southern hemisphere. Finally, monthly trade data may be particularly affected by seasonal inventory or accounting effects. We control for these effects by including country-specific month effects $\rho_{i,m}$, i.e., effects which are constant across all years. These also control for differences in country size and other time-invariant unobservable characteristics at the country(-month) level.

Monthly trade data allow us to document the intra-annual short-run effects of disasters, i.e., the immediate disruption to imports and exports after a disaster hits. Natural disasters may also affect economic growth in the long-run. Regularly occurring natural disasters may imply larger depreciation of capital stocks or lead to lower steady state capital stocks as investment is hampered by potential destruction by disasters. These factors will reduce the long-run steady state growth rate of the economy. Trade flows tend to increase one to one with income, see Head and Mayer (2014). As income growth rates differ across countries, we follow the suggestion by Neumark et al. (2014) and allow for country-specific growth rates in trade flows by including country-specific cubic time trends $\delta_i f(t)$.[20] In addition, we include separate month-year effects η_t to capture world-wide fluctuations in the business cycle. Note that while $\rho_{i,m}$ separates out

[20]In Appendix A, we present results using country-specific linear and quadratic time trends instead.

time-invariant country-specific effects for every of the 12 months of the year, η_t is time-varying, i.e., represents a separate effect for every of the 480 months (40 years $\times$ 12 = 480 observations), which is constrained to be identical across all countries.

As shown by Equation (7), we can interpret the estimated supply effects of a disaster from Equation (8) as $\alpha_k = \Delta\mu_{i,k} = -(1-\sigma)\Delta \ln A_{i,k}$, i.e., our estimated disaster effect in month k after the disaster is observationally equivalent to an exogenous productivity shock in the same month. We can transform the estimated effect in the implied monthly productivity shock by $\Delta \ln A_{i,k} = -\alpha_k/(1-\sigma) = \alpha_k/5.03$, i.e., the estimated coefficient is divided by $-(1-\sigma)$ to get the implied monthly productivity effect. Note that a disaster may also affect the trade infrastructure, hence, it may destroy a harbor or an airport, increasing trade costs for all import source and export destination countries simultaneously. Hence our estimated disaster productivity shock also includes all disaster-related trade cost shocks. From this perspective, whether productivity is lower because machines are destroyed or one has to ship more units due to the higher trade costs is observationally equivalent. Similarly, in the light of Equation (4), we interpret the estimated demand effects of a disaster from Equation (9) as $\beta_k = \Delta\zeta_{j,k} = \Delta \ln E_{i,k} = \Delta \ln(1 + d_{j,k}) \approx \Delta d_{j,k}$ i.e., our estimated disaster effect is observationally equivalent to an exogenous monthly expenditure shock.

Identification of our short-run disaster effects stems from the random occurrence of disasters, conditional on the battery of fixed effects and time trends included in our baseline specification. Our regression model is therefore equivalent to a two-way fixed effect model which relaxes the common trend assumption as our panel structure allows us to identify country-specific trends. We follow the recommendation by Bertrand et al. (2004) and cluster standard errors at the country level.

6.2 Results for Country Groups

To identify the effects of major earthquakes and storms on countries' supply and demand, we include a full year of monthly lags, i.e., twelve months, and one monthly lead, as a simple pre-trend test. We split our sample into credit-constrained countries (CCCs) and non-constrained countries (non-CCCs) to allow for separate disaster effects across the two groups.

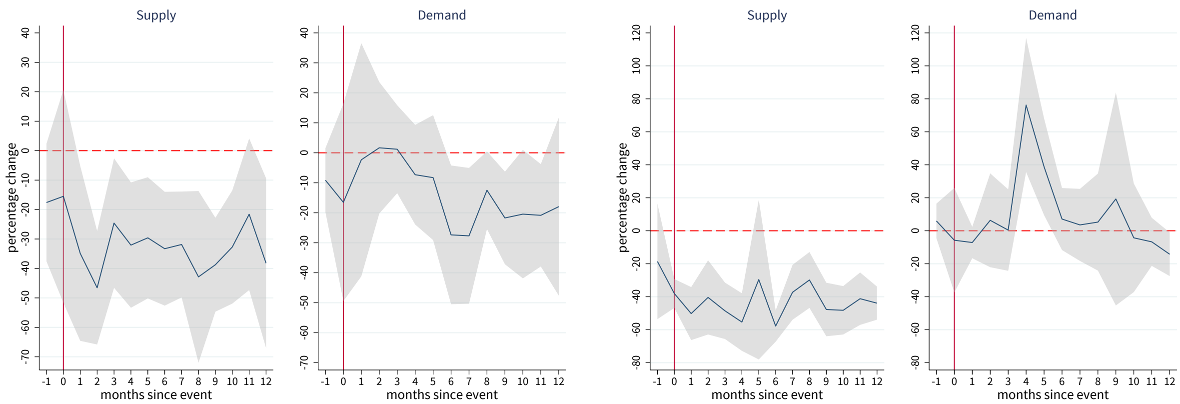
Credit-Constrained Countries. Figure 4 displays the estimated percentage effects of earthquakes and storms in CCCs.[21] Across all figures, one month leads of earthquake or storm events do not show a statistically significant effect for any of the country groups, consistent with the exogeneity of our physical disaster measures.

Panel (a) shows that effects of major earthquakes on CCC supply last at least up to a year after the event. CCC supply drops by 15 percent in the month of the earthquake, and declines by

[21] We present the underlying regression coefficients in Table A4 in the Appendix.

Figure 4: Effects of Disasters in Credit-Constrained Countries (1980-2014), in Percent

(a) **Earthquakes** (b) **Storms**



Notes: Figures show estimated percentage change effects of earthquakes on monthly supply and demand. Percentage changes are calculated as $(\exp(\beta_k) - 1) \times 100$. 95% confidence intervals are calculated using the delta method. Parameter estimates β_k are taken from Table A4 columns (1) and (5) in the Appendix. One monthly lead and twelve monthly lags depicted on horizontal axis.

47 percent two months after the event. These significant and negative effects persist up to 12 months after the event, fluctuating around a 30 percent drop. Demand effects in CCCs after an earthquake are either non-significant or negative, with significant negative effects up to 11 months after the event. In any case, our results clearly rule out demand increases in CCCs after an earthquake. This suggests that permanent income is reduced by unexpected earthquakes.

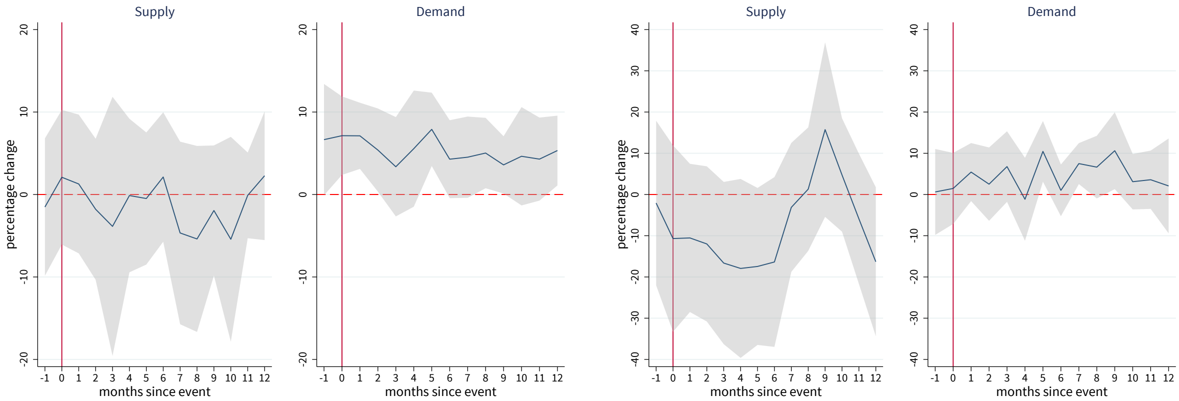
Panel (b) of Figure 4 turns to storms. It finds persistent negative and significant reductions in supply of CCCs, with -38 percent in the month of the event and around -40 percent throughout the 12 months after. Again, we do not find statistically significant effects on demand of CCCs in the wake of a storm, with the exception of a short positive effect of 76 percent 4 month after the event.

Summarizing, we may say that major earthquakes and storms have very substantial and persistent negative effects on the supply capacity of CCCs. On the demand side, the picture is less clear, but there is some evidence of permanently reduced demand after a short-run build-back effect.

Non-Credit-Constrained Countries. Figure 5 turns to countries that can borrow and lend relatively freely on international markets. Earthquakes do not significantly affect supply in non-CCCs. For storms, there is some weak evidence for negative short-run effect, but the point estimates are only marginally significant in the period from four to six months after the event. In contrast, we find positive point estimates of import demand effects of earthquakes and storms (with the exception of a small negative effect 4 months after storms), consistent with an increase in imports to rebuild destroyed infrastructure and to replace destroyed capital stocks, but estimates are mostly not significant. Broadly, our results are consistent with the idea that non-credit-constrained countries can increase imports to quickly repair supply-side damage and that the long-run consequences of major disasters are relatively small.

Figure 5: Effects of Major Disasters in Non-Credit-Constrained Countries (1980-2014), in Percent

(a) **Earthquakes** (b) **Storms**



Notes: Figures show estimated percentage change effects of earthquakes on monthly supply and demand. Percentage changes are calculated as $(\exp(\beta_k) - 1) \times 100$. 95% confidence intervals are calculated using the delta method. Parameter estimates β_k are taken from Table A4 columns (2) and (6) in the Appendix. One monthly lead and twelve monthly lags depicted on horizontal axis.

Robustness. In our baseline regression, we use a cubic country-specific time trend to control for non-linear trends in the trade data. To check the robustness of the estimated demand and supply effects, we also use linear and quadratic country-specific time trends for $\delta_i f(t)$. Table A5 in the Appendix presents the results. We use a linear trend in Panel A and a quadratic trend in Panel B. In Panel A, we find very similar results in sign to our baseline both for the CCC and the non-CCC split sample, magnitudes are slightly smaller compared to our baseline. Again, CCCs are on average more strongly affected than non-CCCs both through major earthquakes and storms. The same is true for Panel B, sign and magnitude of our results are very close to our baseline both for the CCC and non-CCC sample.

6.3 Results for Individual Disasters

The relatively large confidence intervals in the previous section hint at a high level of heterogeneity in the effects of disasters, even within the group of CCCs and non-CCCs, whereas our regressions so far assume homogeneous treatment effects for all disaster events of the same type. In this section, we therefore quantify the dynamics of the supply and demand effects of individual disasters. We focus on the earthquake which hit Nicaragua, a credit-constrained country[22], in September 1992 and the Tohoku earthquake which hit Japan, a non-credit-constrained country, in March 2011.

The 1992 Nicaragua earthquake hit the country with a magnitude of 7.7 M_w in the beginning of September 1992, and created a tsunami where none was expected; for details see Arcos et al. (2017). It was the strongest seismic event to occur in Nicaragua in 20 years. The tsunami mostly affected the west coast of Nicaragua and reached heights up to 9.9 meters—it was disproportionately large and unusually long for its size. It ran inland up to 1,000 meters. The total damage in Nicaragua was estimated at between 20 to 30 million U.S. dollars.[23]

The Tohoku earthquake hit Japan in March 2011 with a magnitude of 9.1 M_w. It was the most powerful earthquake ever recorded in Japan. The quake triggered a tsunami that reached heights of up to 40.5 meters and traveled up to 10,000 meters inland. The economic cost of the disaster is estimated to be 210 billion U.S. dollar, see Ranghieri and Ishiwatari (2014), making it the costliest natural disaster in history.

To get the supply and demand effects of these specific disasters, we reestimate Equations (8) and (9) to uncover the demand and supply effects of these individual disasters by replacing the earthquake and storm dummies by indicator variables in the month and year of occurrence of the disaster in the specific country. We report estimates for the effects of disasters up to two years (24 months) after the event, assuming a constant effect of the disaster within a quarter (3 months).[24] To avoid pollution of our estimates by other earthquakes which may occur before or after the events we are focussing on, all our specifications also include (unreported) dummies to control for other earthquakes in Nicaragua or Japan of magnitude 6 (strong events that cause a lot of damage in very populated areas as classified by UPSeis) and higher, as well as earthquakes that fall within the five percent largest earthquakes during the observed time period in these countries. We present results in Figure 6 for Nicaragua and in Figure 7 for Japan.[25]

For both events, export supply falls considerably in the month of the earthquake and tsunami as well as the subsequent three months, but to a much larger extent in Nicaragua. Nicaragua's supply falls by 37 percent in the month of the earthquake and remains 46 to 22 percent lower, showing a persistent negative effect on supply up to 24 months after the event (see column (1)

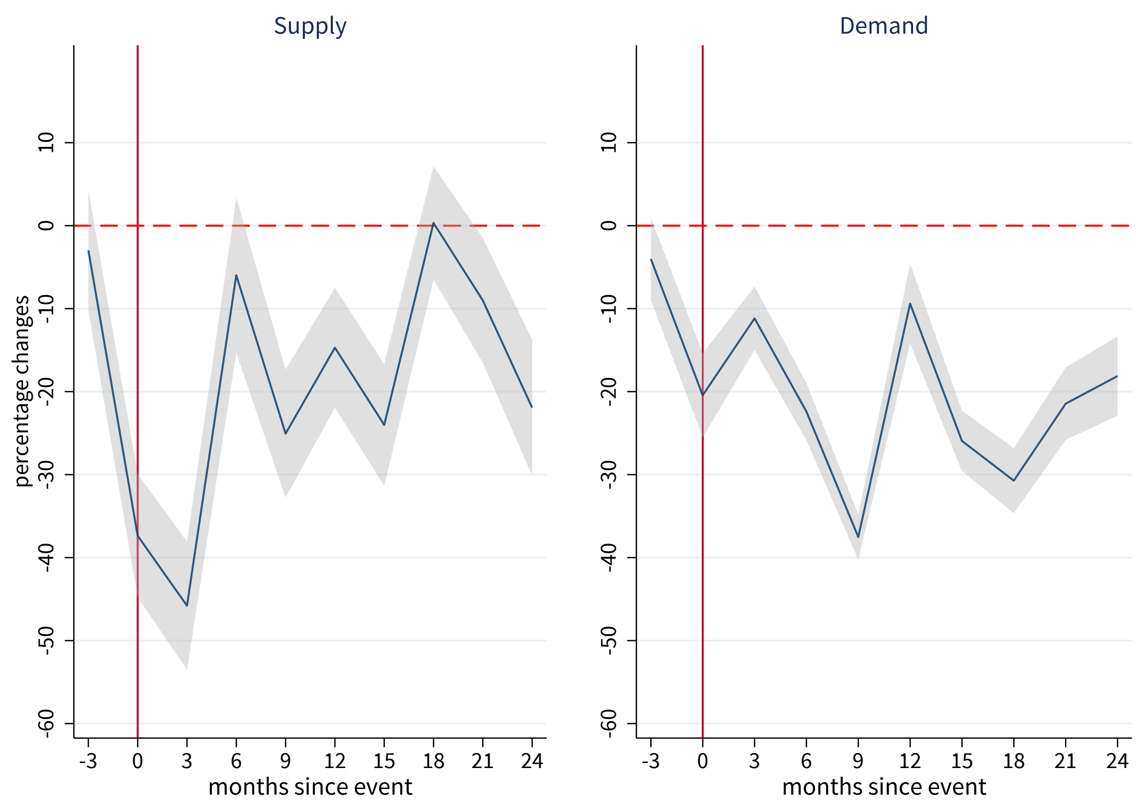
[22]External debt in percent of Gross National Income in Nicaragua amounted to 1233.1 percent in 1989 and was reduced but still stood at 879.2 percent in 1992 when the earthquake and tsunami struck the country. Nicaragua's short-term debt as a percent of exports of goods, services and primary income was 501.5 percent in 1991 and increased to 585.5 percent in 1992, the year of the disaster.

[23]For details see the United States Geological Survey `https://web.archive.org/web/20090912001941/http://earthquake.usgs.gov/eqcenter/eqarchives/significant/sig_1992.php`.

[24]As we found persistent and significant effects towards the end of the twelve months window, we moved to allowing for effects up to two years but assuming constancy of effects within a quarter. This avoids near collinearity problems we encountered in unreported regressions which included 24 individual month dummies. We report regressions using the same specification as Table A4, i.e., allowing for different disaster effects for every of the twelve months after the disaster, in Table A7 in the Appendix.

[25]Table A6 in the Appendix provides the coefficient estimates underlying Figures 6 and 7.

Figure 6: Earthquake, Nicaragua, 09/1992



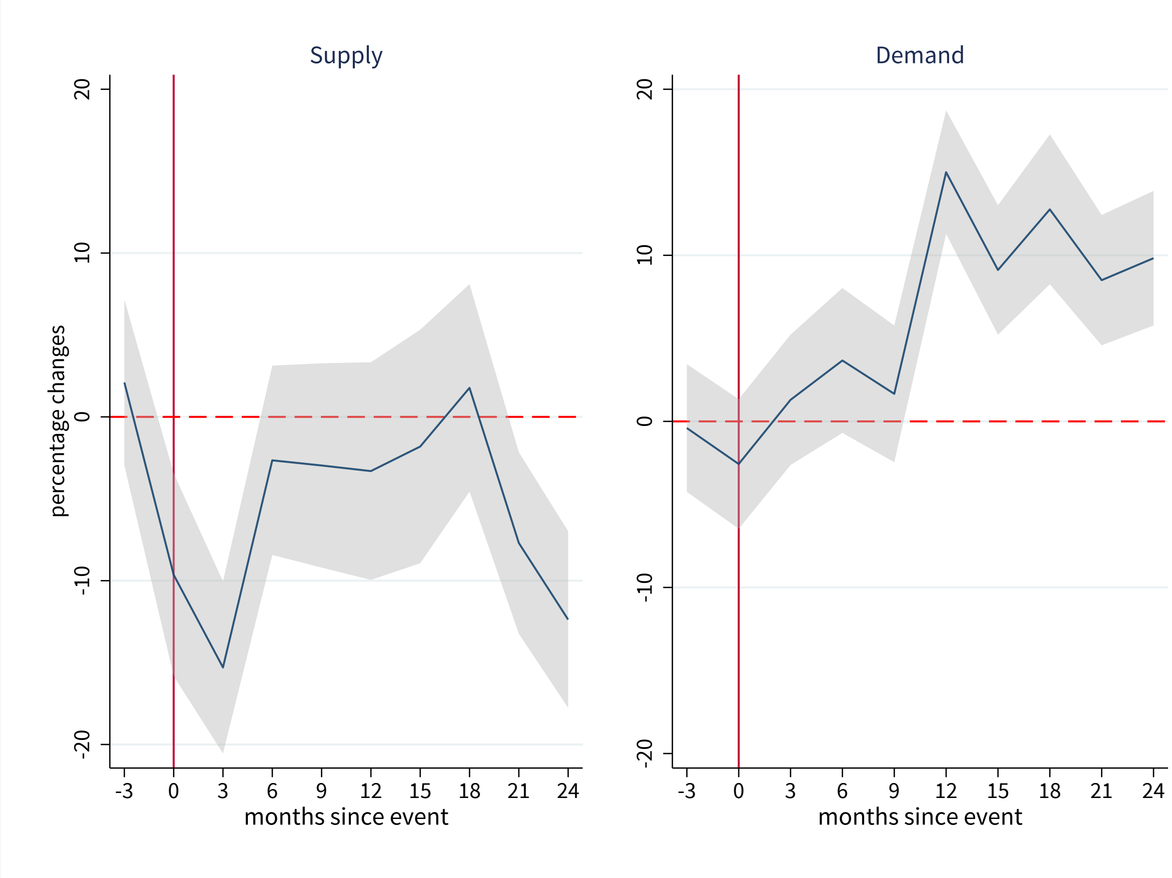
Notes: Figures show estimated percentage change effects of the Nicaragua earthquakes on supply and demand. Percentage changes are calculated as $(\exp(\beta_k) - 1) \times 100$. 95% confidence intervals are calculated using the delta method. Parameter estimates β_k are taken from Table A6 columns (1) and (3) in the Appendix. Control events include earthquakes in Nicaragua above a magnitude of six Richter and within the top five percent of earthquakes within the observed time frame. Three- monthly (quarterly) lead and 24 (quarterly) monthly lags depicted on horizontal axis.

of Table A6). Contrary to that, the Tohoku earthquake's (column (2)) supply effects are much smaller: From 10 percent in the month of the event to 15 percent three months after the event. Then, point estimates of supply effects are less than 3 percent and no longer significant, with the exception of 21 to 24 months after the event.

Turning to the demand side, the Nicaragua earthquake (column (3)) has reduced import demand by 20 percent in the immediate month of the disaster. Demand effects stay consistently negative and significant up to 24 months after the event, with the largest negative effect after 9 months of -38 percent. After that, demand is at least 9 percent lower up to 24 months after the earthquake and tsunami hit in September 1992, in line with the prediction of our model for credit-constrained countries.

This is in stark contrast to the demand effects in Japan: We find no significant reduction of demand in the month of the earthquake or thereafter (column (4)). Instead, import demand

Figure 7: Tohoku Earthquake, Japan, 03/2011



Notes: Figures show estimated percentage change effects of the Tohoku earthquakes on supply and demand. Percentage changes are calculated as $(\exp(\beta_k) - 1) \times 100$. 95% confidence intervals are calculated using the delta method. Parameter estimates β_k are taken from Table A6 columns (1) and (3) in the Appendix. Control events include earthquakes in Japan above a magnitude of six Richter and within the top five percent of earthquakes within the observed time frame. Three-monthly (quarterly) lead and 24 (quarterly) monthly lags depicted on horizontal axis.

increases: for the first 9 months, not significantly, but by 15 percent 12 months after the event, and then around 10 percent in the second year after the event. Our results are consistent with our model which predicts an increase of demand to rebuild destroyed infrastructure and capital goods in non-credit-constrained countries. This contrasts with the experience of Nicaragua, which saw its demand decrease for the whole of two years after the event. This probably reflects Nicaragua's lack of access to financial markets to finance rebuilding destroyed capital. In Japan, despite the massive damage of the earthquake and tsunami, many more firms and households are insured and Japan is able to access international financial markets despite its location in an earthquake-prone region.

As expected, confidence intervals of our event-specific estimates are much tighter, highlighting the benefit of studying the effects of individual disasters. Overall, our results confirm theoretical predictions: While demand falls after a disaster in a credit-constrained country like Nicaragua, it increases in a non-credit-constrained country like Japan. These results also highlight that studies using only aggregate statistics such as GDP growth to identify the effects of disasters will give the wrong impression of their complex demand and supply effects.

7 Welfare Effects, Trade Costs, and International Spillovers

In our analysis of the supply and demand effects of disasters, we have so far only relied on the decomposition of bilateral trade flows into their components via a standard gravity model by using Equation (5). By taking our structural model in Section 2 seriously, and by using our estimated productivity parameters from Section 5, we can go a step further: This allows us to study how disasters impact not only the affected country itself but also its trade partners, and how these spillovers are determined by trade costs and country size. To do so, we use the standard macroeconomic closure condition behind all state of the art quantitative trade models that per period income of a country equals sales to both final consumers and intermediate goods producers across all trade partners, including the country itself.[26] The model also allows us to measure the welfare effects of natural disasters, where welfare in the context of the model of a constant labor force is synonymous to real wage effects. We describe the closure and solution of the model in Section A in the Appendix.

We continue with our study of the earthquakes in Nicaragua and Japan. For each disaster event, we use the estimated supply and demand effects from Table A6, i.e., the estimates underlying Figures 6 and 7, to identify the associated changes in monthly productivity and expenditure, $\Delta A_{i,t}$ and $\Delta d_{i,t}$. We then calculate the implied per period welfare changes compared to a counterfactual scenario where the disaster had not happened. Note that we report monthly effects. As our regression estimates assume constant effects within each quarter, we only report the effects for one month in each quarter.

We present results for Japan in Table 2. Its first three columns show monthly welfare effects using observed trade costs, i.e., using the estimated trade cost parameters reported in Section 4. The first column presents the results when we shock the economy only by the estimated supply effect (only $\Delta A_{i,t}$), the second column when we only use the estimated demand effect (only $\Delta d_{i,t}$), and the third column reports results of the combined supply and demand effect ($\Delta A_{i,t}$ & $\Delta d_{i,t}$). Comparing the three columns makes clear that both the supply and the demand shock can have substantial effects. Importantly, the effects can have opposite directions, showing the complex effects of natural disasters on supply and demand.

Why are welfare effects so large? First, remember that we show monthly results. Therefore, we report the same results but annualized (divided by 12) in Table A8 in the Appendix to see how the disaster affects annual real income. Second, we follow Eaton and Kortum (2002) and

[26]This closure condition is used in the standard quantitative trade models such Anderson and van Wincoop (2003), Eaton and Kortum (2002). For an overview of these models and their relation to gravity models, see Head and Mayer (2014) and Costinot and Rodríguez-Clare (2014).

Table 2: Model-implied Monthly Welfare Effects: Impact of Trade Costs for 03/2011 Tohoku Earthquake, Japan

Event:	**Tohoku Earthquake, Japan**					
	estimated trade costs			no trade costs		
	only supply $\Delta A_{i,t}$	only demand $\Delta d_{i,t}$	supply & demand $\Delta A_{i,t}$ & $\Delta d_{i,t}$	only supply $\Delta A_{i,t}$	only demand $\Delta d_{i,t}$	supply & demand $\Delta A_{i,t}$ & $\Delta d_{i,t}$
Per Period Welfare Effect for Japan						
t	-9.2	-4.7	-13.5	-5.4	-2.8	-8.0
$t+3$	-14.7	2.4	-12.6	-8.7	1.4	-7.5
$t+6$	-2.5	6.8	4.1	-1.5	3.8	2.3
$t+9$	-2.8	3.0	0.2	-1.6	1.7	0.1
$t+12$	-3.1	27.4	23.4	-1.8	15.1	13.0
$t+24$	-11.8	18.0	4.0	-7.0	10.1	2.3
Indirect Welfare Effect on Rest of the World (Median)						
t	-0.4	-0.2	-0.5	-0.6	-0.3	-0.8
$t+3$	-0.6	0.1	-0.5	-0.9	0.1	-0.8
$t+6$	-0.1	0.2	0.1	-0.2	0.4	0.2
$t+9$	-0.1	0.1	-0.0	-0.2	0.2	0.0
$t+12$	-0.1	1.0	0.8	-0.2	1.5	1.3
$t+24$	-0.5	0.6	0.1	-0.7	1.0	0.2

Notes: Table reports model-implied monthly welfare effects in percent, where welfare is measured as monthly real income. t is the month of the disaster event.

Table 3: Model-implied Monthly Welfare Effects: Impact of Trade Costs for 09/1992 Earthquake, Nicaragua

Event:	**Earthquake, Nicaragua**					
	estimated trade costs			no trade costs		
	only supply $\Delta A_{i,t}$	only demand $\Delta d_{i,t}$	supply & demand $\Delta A_{i,t}$ & $\Delta d_{i,t}$	only supply $\Delta A_{i,t}$	only demand $\Delta d_{i,t}$	supply & demand $\Delta A_{i,t}$ & $\Delta d_{i,t}$
Per Period Welfare Effect for Nicaragua						
t	-19.4	-8.2	-26.0	-21.2	-8.2	-27.7
$t+3$	-24.9	-4.2	-28.1	-27.2	-4.2	-30.3
$t+6$	-2.7	-9.0	-11.5	-3.0	-9.0	-11.7
$t+9$	-12.2	-16.8	-26.9	-13.4	-16.8	-28.0
$t+12$	-6.8	-3.5	-10.1	-7.6	-3.5	-10.8
$t+24$	-10.5	-7.1	-16.9	-11.6	-7.1	-17.9

Notes: Table reports model-implied monthly welfare effects in percent, where welfare is measured as monthly real income. t is the month of the disaster event.

set the labor share in production costs $\beta = 0.21$. This corresponds to the value added share of labor in the manufacturing sector in their sample of OECD countries. It implies that 79 percent of production costs are intermediate goods. As intermediate goods are important in the production process, a change in trade translates into large welfare changes. When we set $\beta = 0.51$ in unreported simulations, the average of the labor share across all countries in 2014 using the Penn World Tables 9.1 from Feenstra et al. (2015), our welfare effects shrink by about 20 percent.[27]

Our general equilibrium model also allows us to calculate how the disaster affects welfare in other countries. We report the median effect in all other countries in the sample in the bottom panel of Table 2. While the median effect is relatively small, we find considerable heterogeneity of the size of spillovers across countries, as illustrated by Figure 8. It shows the monthly welfare effects in percent of the Tohoku earthquake in Japan across the world using both the estimated supply and demand effects ($\Delta A_{i,t}$ & $\Delta d_{i,t}$) as well as estimated trade costs in the month of the onset of the disaster. Geographically closer economies, economies with a regional trade agreement with Japan such as the ASEAN member countries, as well as mostly African countries benefiting from Japan's participation in the GSP, are hit harder by the spillover effects relative to other economies.

[27] In our trade model, per period welfare changes can be written as $W_{j,t}^{\text{disaster}}/W_{j,t}^{\text{no disaster}} = (X_{jj,t}^{\text{no disaster}}/X_{jj,t}^{\text{disaster}})^{1/(\beta(1-\sigma))}$, hence the absolute magnitude of the welfare effect becomes smaller the larger the labor cost share, see Eaton and Kortum (2002), p. 1768 and Arkolakis et al. (2012).

Results are different for the 1992 earthquake in Nicaragua. Table 3 presents results for its monthly welfare effects and is organized in the same way as Table 2. Annualized effects are presented in Table A9 in the Appendix. As expected, the larger negative supply and demand effects from Figure 6 translate into larger negative welfare effects. Median spillover effects, however, are consistently zero for all periods and exercises (we therefore omit reporting them in Table 3 to save space).

Why do we find relatively large spillover effects on third countries for the Tohoku earthquake, but no effects on third countries for the Nicaragua earthquake? Anderson and van Wincoop (2003) show that in quantitative trade models such as ours, a country's price level is a weighted average of prices of goods across all import source partners, with the weight being the source country's world expenditure share. Using GDP as a proxy for expenditure, Nicaragua had a world GDP share of 0.007 percent in 1992 in our sample. Hence, goods from Nicaragua make up only a small share in the consumption bundles of the rest of the world, and hence hardly affect other countries.[28] Japan's world GDP share in 2011 was close to 9 percent. Consequently, median spillover effects on other countries are larger, but still quite small, between -0.5 and 0.8 percent ($\Delta A_{i,t}$ & $\Delta d_{i,t}$, estimated trade costs), depending on the month. This is consistent with results by Behar and Nelson (2014) who also find only small general equilibrium spillover effects of bilateral trade cost changes except for large countries. As we simulate the disasters as only hitting one country, the same intuition applies to our setting.[29] Hence a fall in productivity in a small country and subsequent price increase of this country's goods translates only to a small effect in other countries' consumption. Similarly, if a country's imports increase due to the expenditure shock, it increases its demand for goods from all other countries. However, given its small world expenditure share, this increase in demand does hardly increase prices charged by other countries as the small country is not a large enough export market for the rest of the world.

The last three columns of Tables 2 and 3 repeat the previous exercises but now in a counterfactual world where we set all international trade costs between all countries to zero. Note that without trade costs, all countries in the rest of the world face the same spillover effect.[30] It becomes clear that without trade costs, the spillover effects on the rest of the world are larger, whereas the direct effects are considerably smaller (again, median spillover effects of the Nicaragua earthquake are 0 in all scenarios and therefore not reported). This highlights the insurance aspect of international trade: With zero trade costs, Japan can make up for the negative productivity shock easier by importing more goods from abroad. Note that this larger insurance effect for the affected country comes purely from lower trade costs and does not depend on the existence of an actual

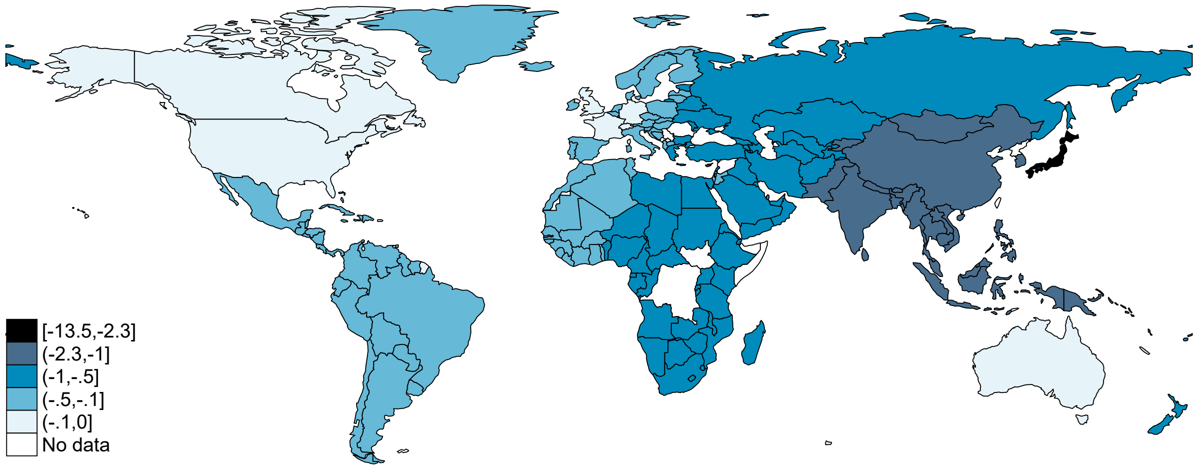
[28] In a world without trade costs and identical preferences, market shares of individual countries are equal to their world expenditure shares, i.e., approximately their GDP shares, see Anderson (2011).

[29] Even if we simulated disaster events hitting neighboring countries simultaneously, as long as the world GDP share of all affected countries is small, results would hardly change.

[30] This is a general feature of quantitative trade models used in the literature with homothetic preferences and is not particular to our model.

insurance against negative shocks such as a disaster. From this perspective, trade liberalization can mitigate the negative effects of natural disasters. The effects can be substantial: The negative welfare effect in the month of the Tohoku earthquake is about 40 percent smaller (-13.5 vs. -8.0 percent, $\Delta A_{i,t}$ & $\Delta d_{i,t}$ in Table 2).

Figure 8: Distribution of Model-Based Spillover Effects of Tohoku Earthquake



Notes: Figure shows the spillover of monthly welfare effects of the Tohoku Earthquake in Japan in the immediate month of the onset of the disaster to the rest of the world in a world with trade costs. The map shows monthly welfare effects in percent.

This insurance effect of lower trade costs, however, is only present for disasters when they hit large economies. For Nicaragua, the insurance effect is absent, and absolute magnitudes in the scenario without trade costs are even slightly larger.[31] Why is this the case? The answer lies in the fact that the insurance effect is due to a terms of trade effect: In a world without trade costs, country size and hence terms of trade effects matter most. If a large country is hit by a negative productivity shock, its export prices increase by less than those of a small open economy, as the large country has a larger impact on other countries' price levels than a small country. At the same time, trade costs ensure that countries with lower productivity can sell goods as they shelter them from more productive but far-away competition. Consequently, when a small country like Nicaragua is hit by a disaster, its negative productivity effect decreases welfare more in a world without trade costs.

8 Conclusion

The economic consequences of natural disasters are still poorly understood. One reason lies in the paucity of data at high frequency, particularly for less and least developed economies. We present a simple quantitative trade model which allows us to identify the short-run supply and

[31]In Table 3, the effects for considering only the demand shock (only demand $\Delta d_{i,t}$) seem to be identical with estimated and with no trade costs. This is not due to an error but due to rounding to the first digit.

demand effects of disasters at a high frequency derived from monthly trade data. Combining a panel of monthly merchandise import and export data with the ifo gridded GAME database of physical intensities of natural disasters, we illustrate our approach by quantifying the effects of two types of short-onset disasters: earthquakes and storms. We document that the economic effects of disasters differ quantitatively and qualitatively across credit-constrained versus non-credit-constrained countries. While non-credit-constrained, developed economies are typically less affected by disasters, least developed, landlocked and heavily indebted and hence credit-constrained countries suffer most. We then apply our framework to two individual disasters, the 1992 earthquake and tsunami in Nicaragua, a credit-constrained country, and the 2011 Tohoku earthquake and tsunami in Japan, a non-credit-constrained country. Our results illustrate that a country's trade costs with its trade partners play a crucial role in determining the size of international spillover effects of disasters.

Our results also highlight the unequal burden of countries in the face of extreme events. The countries most affected have likely the smallest spillover effects on other countries, as they are less integrated in the world economy and are small in terms of their economic size. Besides these equity concerns highlighted by our quantification, our results also show how to respond to such disasters: When negative effects of disasters mostly operate via negative demand, i.e., expenditure effects, disaster relief measures should focus on providing short-term fiscal aid to affected countries in order to alleviate these negative demand shocks, whereas negative supply, i.e., productivity effects point to alleviating the financing needs of the private sector to rebuild destroyed production capacity.

Our quantitative framework produces measures of monthly aggregate productivity from monthly trade data without the need for detailed factor use data. It is therefore simple enough to be applied particularly to countries for which other, more detailed data are not available, or only with considerable time lag or effort. Besides the analysis of natural disasters, our monthly supply, demand, and productivity measures can be applied to many other contexts, e.g., to study the short-run productivity effects of economic policies. More broadly, our study should be seen as a first step towards using trade data to identify aggregate short-run fluctuations in economic activity.

References

Alvarez, F. (2017). Capital Accumulation and International Trade. *Journal of Monetary Economics*, 91:1–18.

Anderson, J. E. (2011). The Gravity Model. *Annual Review of Economics*, 3(1):133–160.

Anderson, J. E., Larch, M., and Yotov, Y. V. (2020). Transitional growth and trade with frictions: A structural estimation framework. *Economic Journal*, 130(630):1583–1607.

Anderson, J. E. and van Wincoop, E. (2003). Gravity with Gravitas: A Solution to the Border Puzzle. *American Economic Review*, 93(1):170–192.

Anderson, J. E. and Yotov, Y. V. (2016). Terms of Trade and Global Efficiency Effects of Free Trade Agreements, 1990-2002. *Journal of International Economics*, 99:279–298.

Arcos, N., Dunbar, P., Stroker, K., and Kong, L. (2017). The Legacy of the 1992 Nicaragua Tsunami. *Eos*, 98:n.p.

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

Armington, P. S. (1969). A Theory of Demand for Products Distinguished by Place of Production. *Staff Papers - International Monetary Fund*, 16(1):159–178.

Auffhammer, M. (2018). Quantifying Economic Damages from Climate Change. *Journal of Economic Perspectives*, 32(4):33–52.

Baier, S. L., Bergstrand, J. H., and Feng, M. (2014). Economic Integration Agreements and the Margins of International Trade. *Journal of International Economics*, 93(2):339–350.

Barrot, J.-N. and Sauvagnat, J. (2016). Input Specificity and the Propagation of Idiosyncratic Shocks in Production Networks. *Quarterly Journal of Economics*, 131(3):1543–1592.

Baxter, M. and King, R. G. (1999). Measuring business cycles: Approximate band-pass filters for economic time series. *Review of Economics and Statistics*, 81(4):575–593.

Behar, A. and Nelson, B. D. (2014). Trade Flows, Multilateral Resistance, and Firm Heterogeneity. *Review of Economics and Statistics*, 96(3):538–549.

Berlemann, M. and Wenzel, D. (2018). Hurricanes, economic growth and transmission channels. *World Development*, 105:231–247.

Bertrand, M., Duflo, E., and Mullainathan, S. (2004). How Much Should We Trust Differences-in-Differences Estimates? *Quarterly Journal of Economics*, 119(1):249–275.

Boehm, C. E., Flaaen, A., and Pandalai-Nayar, N. (2019). Input Linkages and the Transmission of Shocks: Firm-level Evidence from the 2011 Tohoku Earthquake. *Review of Economics and Statistics*, 101(1):60–75.

Burgess, R. and Donaldson, D. (2010). Can Openness Mitigate the Effects of Weather Shocks? Evidence from India's Famine Era. *American Economic Review: Papers & Proceedings*, 100(2):449–453.

Carvalho, V. M., Nirei, M., Saito, Y. U., and Tahbaz-Salehi, A. (2021). Supply Chain Disruptions: Evidence from the Great East Japan Earthquake. *Quarterly Journal of Economics*, 136(2):1255–1321.

Cavallo, A., Cavallo, E., and Rigobon, R. (2014). Prices and Supply Disruptions during Natural Disasters. *Review of Income and Wealth*, 60(S2):S449–S471.

Cavallo, E. and Noy, I. (2011). Natural disasters and the economy - a survey. *International Review of Environmental and Resource Economics*, 5(1):63–102.

Chang, S. E. (2000). Disasters and transport systems: Loss, recovery and competition at the Port of Kobe after the 1995 earthquake. *Journal of Transport Geography*, 8(1):53–65.

Christiano, L. J. and Fitzgerald, T. J. (2003). The band pass filter. *International Economic Review*, 44(2):435–465.

Costinot, A., Donaldson, D., and Komunjer, I. (2012). What Goods Do Countries Trade? A Quantitative Exploration of Ricardo's Ideas. *Review of Economic Studies*, 79(2):581–608.

Costinot, A., Donaldson, D., and Smith, C. B. (2016). Evolving Comparative Advantage and the Impact of Climate Change in Agricultural Markets: Evidence from 1.7 Million Fields around the World. *Journal of Political Economy*, 124(1):205–248.

Costinot, A. and Rodríguez-Clare, A. (2014). Trade Theory with Numbers: Quantifying the Consequences of Globalization. In Gopinath, G., Helpman, E., and Rogoff, K., editors, *Handbook of International Economics Volume 4*, pages 197–261. North-Holland, Amsterdam.

De Mel, S., McKenzie, D., and Woodruff, C. M. (2012). Enterprise recovery following natural disasters. *Economic Journal*, 122(559):64–91.

Dekle, R., Eaton, J., and Kortum, S. (2008). Global Rebalancing with Gravity: Measuring the Burden of Adjustment. *IMF Staff Papers*, 55(3):511–540.

Dell, M., Jones, B. F., and Olken, B. A. (2014). What Do We Learn from the Weather? The New Climate-Economy Literature. *Journal of Economic Literature*, 52(3):740–798.

Eaton, J. and Kortum, S. (2002). Technology, Geography, and Trade. *Econometrica*, 70(5):1741–1779.

Eaton, J., Kortum, S., Neiman, B., and Romalis, J. (2016). Trade and the Global Recession. *American Economic Review*, 106(11):3401–3438.

Egger, P. H. and Nigai, S. (2015). Structural gravity with dummies only: Constrained ANOVA-type estimation of gravity models. *Journal of International Economics*, 97(1):86–99.

Fally, T. (2015). Structural gravity and fixed effects. *Journal of International Economics*, 97(1):76–85.

Feenstra, R. C., Inklaar, R., and Timmer, M. P. (2015). The next generation of the Penn World Table. *American Economic Review*, 105(10):3150–3182.

Felbermayr, G. and Gröschl, J. (2013). Natural disasters and the effect of trade on income: A new panel IV approach. *European Economic Review*, 58(February):18–30.

Felbermayr, G. and Gröschl, J. (2014). Naturally negative: The growth effects of natural disasters. *Journal of Development Economics*, 111:92–106.

Felbermayr, G., Gröschl, J., Sanders, M., Schippers, V., and Steinwachs, T. (2018). Shedding Light on the Spatial Diffusion of Disasters. *CESifo Working Paper 7146*.

Fernald, J. (2014). A Quarterly, Utilization-Adjusted Series on Total Factor Productivity. *Federal Reserve Bank of San Francisco Working Paper 2012-19*.

Gassebner, M., Keck, A., and Teh, R. (2010). Shaken, not stirred: The impact of disasters on international trade. *Review of International Economics*, 18(2):351–368.

Geiger, T., Frieler, K., and Bresch, D. N. (2018). A global historical data set of tropical cyclone exposure (TCE-DAT). *Earth System Science Data*, 10:185–194.

Gibson, J., Olivia, S., Boe-Gibson, G., and Li, C. (2021). Which night lights data should we use in economics, and where? *Journal of Development Economics*, 149:102602.

Head, K. and Mayer, T. (2014). Gravity equations: workhorse, toolkit, and cookbook. In Gopinath, G., Helpman, E., and Rogoff, K., editors, *Handbook of International Economics. Volume 4*, pages 131–190. Elsevier B.V., Amsterdam.

Head, K. and Ries, J. (2008). FDI as an Outcome of the Market for Corporate Control: Theory and Evidence. *Journal of International Economics*, 74(1):2–20.

Heid, B. and Larch, M. (2016). Gravity with unemployment. *Journal of International Economics*, 101:70–85.

Heid, B., Larch, M., and Yotov, Y. (2021). Estimating the Effects of Non-discriminatory Trade Policies within Structural Gravity Models. *Canadian Journal of Economics (forthcoming).*

Heinen, A., Khadan, J., and Strobl, E. (2018). The Price Impact of Extreme Weather in Developing Countries. *Economic Journal*, 129(619):1327–1342.

Hsiang, S. M. and Jina, A. S. (2014). The Causal Effect of Environmental Catastrophe on Long-Run Economic Growth: Evidence from 6,700 Cyclones. *NBER Working Paper 20352.*

Kahn, M. E. (2005). The Death Toll from Natural Disasters: The Role of Income, Geography, and Institutions. *Review of Economics and Statistics*, 87(May):271–284.

Loayza, N. V., Olaberría, E., Rigolini, J., and Christiaensen, L. (2012). Natural Disasters and Growth: Going Beyond the Averages. *World Development*, 40(7):1317–1336.

Mayer, T. and Zignago, S. (2011). Notes on CEPII's Distances Measures: The GeoDist Database. *CEPII Working Paper 2011 - 25.*

Melecky, M. and Raddatz, C. (2015). Fiscal responses after catastrophes and the enabling role of financial development. *World Bank Economic Review*, 29(1):129–149.

Neumark, D., Salas, J. I., and Wascher, W. (2014). Revisiting the Minimum Wage-Employment Debate: Throwing Out the Baby with the Bathwater? *Industrial & Labor Relations Review*, 67(3):608–648.

Noy, I. (2009). The macroeconomic consequences of disasters. *Journal of Development Economics*, 88(2):221–231.

Noy, I. and Nualsri, A. (2011). Fiscal storms: public spending and revenues in the aftermath of natural disasters. *Environment and Development Economics*, 16(1):113–128.

Oh, C. H. and Reuveny, R. (2010). Climatic natural disasters, political risk, and international trade. *Global Environmental Change*, 20(2):243–254.

Olivero, M. P. and Yotov, Y. V. (2012). Dynamic Gravity: Endogenous Country Size and Asset Accumulation. *Canadian Journal of Economics*, 45(1):64–92.

Ramey, V. A. (2016). Macroeconomic Shocks and Their Propagation. In Taylor, J. B. and Uhlig, H., editors, *Handbook of Macroeconomics*, volume 2A, pages 71–162. Elsevier.

Ranghieri, F. and Ishiwatari, M., editors (2014). *Learning from Megadisasters. Lessons from the Great East Japan Earthquake.* The World Bank.

Redding, S. J. and Venables, A. J. (2004). Economic geography and international inequality. *Journal of International Economics*, 62(1):53–82.

Runyan, R. C. (2006). Small business in the face of crisis: Identifying barriers to recovery from a natural disaster. *Journal of Contingencies and Crisis Management*, 14(1):12–26.

Samuelson, P. A. (1954). The Transfer Problem and Transport Costs, II: Analysis of Effects of Trade Impediments. *Economic Journal*, 64(254):264–289.

Santos Silva, J. M. and Tenreyro, S. (2006). The Log of Gravity. *Review of Economics and Statistics*, 88(4):641–658.

Shughart II, W. F. (2006). Katrinanomics: The politics and economics of disaster relief. *Public Choice*, 127(1):31–53.

Strobl, E. (2011). The Economic Growth Impact of Hurricanes: Evidence from U.S. Coastal Counties. *Review of Economics and Statistics*, 93(2):575–589.

Strobl, E. (2012). The economic growth impact of natural disasters in developing countries: Evidence from hurricane strikes in the Central American and Caribbean regions. *Journal of Development Economics*, 97(1):130–141.

Todo, Y., Nakajima, K., and Matous, P. (2015). How do supply chain networks affect the resilience of firms to natural disasters? Evidence from the great east Japan Earthquake. *Journal of Regional Science*, 55(2):209–229.

Toya, H. and Skidmore, M. (2007). Economic development and the impacts of natural disasters. *Economics Letters*, 94(1):20–25.

UNDRR and CRED (2020). *Human cost of disasters: an overview of the last 20 years 2000-2019.* New York: United Office for Disaster Risk Reduction.

Yotov, Y. V., Larch, M., Monteiro, J.-A., and Piermartini, R. (2016). *An Advanced Guide to Trade Policy Analysis: The Structural Gravity Model.* United Nations and World Trade Organization, Geneva, Switzerland, available for download at http://vi.unctad.org/tpa/index.html.

For Online Publication
Appendix for "Quantifying the Supply and Demand Effects of Natural Disasters Using Monthly Trade Data"

Gabriel Felbermayr[1], Jasmin Gröschl[2] and Benedikt Heid[3]

June 24, 2021

A Closing the General Equilibrium Model

Our model implies that the dynamic choices of households boil down to the decision on how much to spend on consumption in each period. Conditional on the amount of expenditure per period, our dynamic model collapses into a sequence of static problems of how much to consume from each country. In general equilibrium, current period income equals sales to both final consumers and intermediate goods producers, i.e.,

$$Y_{i,t} = \sum_{j=1}^{N} X_{ij,t} = w_{i,t}L_{i,t} + (1-\beta)Y_{i,t}, \tag{A.1}$$

where $w_{i,t}L_{i,t}$ is the wage bill paid to the labor force $L_{i,t}$ and β is the labor cost share. For our counterfactual simulations, we follow Eaton and Kortum (2002) and set the labor share in production costs, β, equal to 0.21. We can solve this for total sales which yields $Y_{i,t} = w_{i,t}L_{i,t}/\beta$. We also know that sales income plus the trade deficit equals expenditure, i.e., $E_{i,t} = (1 + d_{i,t})w_{i,t}L_{i,t}$, and $d_{i,t}$ is the size of the trade deficit expressed as a percentage of sales income.

[1]Felbermayr, IfW Kiel Institute for the World Economy, Kiellinie 66, 24105 Kiel, Germany; Christian-Albrechts-Universität zu Kiel, CESifo and GEP; gabriel.felbermayr@ifw-kiel.de. [2]Gröschl, Ifo Institute – Leibniz Institute for Economic Research at the University of Munich, Poschingerstr. 5, 81679 Munich, Germany; University of Munich and CESifo; groeschl@ifo.de. [3]Heid, University of Adelaide and CESifo. Address: School of Economics and Public Policy, University of Adelaide, 10 Pulteney St, 5005 SA, Australia. Phone: +61 88313 4930. Email: benedikt.heid@adelaide.edu.au. [◇]We thank participants at the School of Economics Seminar at the University of Utrecht, IPAG Business School in Paris, ETSG 2017 in Florence, ATW 2018 in Auckland, the CESifo Venice Summer Institute 2019 and the CESifo Global Area Conference 2020 for fruitful discussions, useful comments and suggestions. Jasmin Gröschl gratefully acknowledges funding from the German Research Foundation (DFG) under project GR4896/1-1 and the hospitality of the School of Economics at the University of Adelaide during a research visit. Benedikt Heid gratefully acknowledges funding from the Australian Research Council (ARC) under project DP190103524. We thank Saskia Mösle for excellent help with the industrial production data. All remaining errors are our own.

Hence we can write

$$Y_{it} = \sum_{j=1}^{N} X_{ij,t} = \left(\frac{a_i c_{i,t}}{P_{j,t}}\right)^{1-\sigma} E_{j,t} \tag{A.2}$$

$$\frac{w_{i,t}L_{i,t}}{\beta} = \sum_{j=1}^{N} X_{ij,t} = (a_i c_{i,t})^{1-\sigma} \sum_{j=1}^{N} \left(\frac{t_{ij,t}}{P_j}\right)^{1-\sigma} (1+d_{j,t})[w_{j,t}L_{j,t} + (1-\beta)Y_{j,t}] \tag{A.3}$$

$$w_{i,t}L_{i,t} = \sum_{j=1}^{N} X_{ij,t} = (a_i c_{i,t})^{1-\sigma} \sum_{j=1}^{N} \left(\frac{t_{ij,t}}{P_j}\right)^{1-\sigma} (1+d_{j,t})w_{j,t}L_{j,t}, \tag{A.4}$$

where the last line again used $Y_{i,t} = w_{i,t}L_{i,t}/\beta$. Given the exogenous parameters, Equation (A.4) jointly with the definition of the price index, $P_{j,t} = \left(\sum_{i=1}^{N} p_{ij,t}^{1-\sigma}\right)^{\frac{1}{1-\sigma}}$, and the pricing equation, $p_{i,t} = c_{i,t} = \frac{1}{A_{i,t}} w_{i,t}^{\beta} P_{i,t}^{1-\beta}$, determine N endogenous wages $w_{j,t}$ at time t from which we can calculate prices, and per period welfare. To quantify the effect of a disaster on welfare, we can solve this system of equations once in a baseline scenario where the disaster took place, and once in a counterfactual scenario where the disaster did not happen. For this, we have to know by how much the parameters of the model would change in the absence of the disaster. We use the estimated effects of disasters on supply and demand to infer the percentage changes $A_{i,t}$ and $d_{i,t}$ as explained in Section 6.1 in the main text.

To solve the system of equations given by Equation (A.4) in the main text in both the baseline and counterfactual scenario, we need not only values of the changes in the parameters but also their levels. While our solution method needs estimates of the level of parameters of our model, a key advantage of our approach is that it circumvents the need for data on domestic trade and production levels which are not available at a monthly frequency.[1] We obtain estimated trade costs, t_{ijt}, from our estimates from Equation (5). We set $t_{iit} = 1 \,\forall\, i, t$, following the standard approach in the gravity literature, see Yotov et al. (2016). We set $(1-\sigma) = -5.03$, the preferred estimate of Head and Mayer (2014), p. 165. Trade deficits, $d_{j,t}$ and population size $L_{j,t}$ are directly observed in the data. We obtain values for the productivity levels, $A_{i,t}$, according to Equation (7) in the main text.

References

Dekle, R., Eaton, J., and Kortum, S. (2008). Global Rebalancing with Gravity: Measuring the Burden of Adjustment. *IMF Staff Papers*, 55(3):511–540.

Eaton, J. and Kortum, S. (2002). Technology, Geography, and Trade. *Econometrica*, 70(5):1741–1779.

[1] Note that the absence of monthly domestic trade and production data prevents us to use the method of Dekle et al. (2008) which does not need estimates of the level of parameters as it relies on the availability of domestic consumption shares.

Head, K. and Mayer, T. (2014). Gravity equations: workhorse, toolkit, and cookbook. In Gopinath, G., Helpman, E., and Rogoff, K., editors, *Handbook of International Economics. Volume 4*, pages 131–190. Elsevier B.V., Amsterdam.

Yotov, Y. V., Larch, M., Monteiro, J.-A., and Piermartini, R. (2016). *An Advanced Guide to Trade Policy Analysis: The Structural Gravity Model.* United Nations and World Trade Organization, Geneva, Switzerland, available for download at http://vi.unctad.org/tpa/index.html.

Further Tables and Figures

Table A1: Summary Statistics, Monthly (1980 - 2014)

Variable	**Observations**	**Mean**	**St. Dev.**	**Min.**	**Max.**
$\ln \mu_{i,t}$	68,978	3.631	2.331	-4.573	9.794
$\ln \zeta_{i,t}$	68,978	4.120	1.879	-3.250	10.189
Non-CCCs, i.e., $[1 - \mathcal{I}(i \text{ can borrow})]$	68,978	0.623	0.485	0.000	1.000
CCCs, i.e., $\mathcal{I}(i \text{ can borrow})$	68,978	0.377	0.485	0.000	1.000
Earthquake, Indicator ($EQ_{i,t}$)	68,978	0.002	0.041	0.000	1.000
Storm, Indicator ($ST_{i,t}$)	68,978	0.001	0.033	0.000	1.000
$EQ_{i,t} \times \mathcal{I}(i \text{ can borrow})$	68,978	0.002	0.040	0.000	1.000
$EQ_{i,t} \times [1 - \mathcal{I}(i \text{ can borrow})]$	68,978	0.000	0.011	0.000	1.000
$ST_{i,t} \times \mathcal{I}(i \text{ can borrow})$	68,978	0.001	0.030	0.000	1.000
$ST_{i,t} \times [1 - \mathcal{I}(i \text{ can borrow})]$	68,978	0.000	0.013	0.000	1.000

Table A2: Country Samples (1980 - 2014)

Country	CCCs	non-CCCs	Country	CCCs	non-CCCs
Afghanistan	1	0	El Salvador	0	1
Albania	0	1	Equatorial Guinea	1	0
Algeria	0	1	Eritrea	1	0
Angola	1	0	Estonia	0	1
Antigua and Barbuda	0	1	Ethiopia	1	0
Argentina	0	1	Fiji	0	1
Armenia	1	0	Finland	0	1
Aruba	1	0	France	0	1
Australia	0	1	Gabon	0	1
Austria	0	1	Gambia, The	1	0
Azerbaijan	1	0	Georgia	0	1
Bahamas, The	0	1	Germany	0	1
Bahrain	0	1	Ghana	1	0
Bangladesh	1	0	Greece	0	1
Barbados	0	1	Grenada	0	1
Belarus	0	1	Guatemala	0	1
Belgium	0	1	Guinea	1	0
Belize	0	1	Guinea-Bissau	1	0
Benin	1	0	Guyana	1	0
Bhutan	1	0	Haiti	1	0
Bolivia	1	0	Honduras	1	0
Bosnia and Herzegovina	0	1	Hong Kong	0	1
Botswana	1	0	Hungary	0	1
Brazil	0	1	Iceland	0	1
Bulgaria	0	1	India	0	1
Burkina Faso	1	0	Indonesia	0	1
Burundi	1	0	Iran	0	1
Cambodia	1	0	Iraq	0	1
Cameroon	1	0	Ireland	0	1
Canada	0	1	Israel	0	1
Cape Verde	1	0	Italy	0	1
Central African Republic	1	0	Jamaica	0	1
Chad	1	0	Japan	0	1
Chile	0	1	Jordan	0	1
China	0	1	Kazakhstan	1	0
Colombia	0	1	Kenya	0	1
Comoros	1	0	Kiribati	1	0
Congo, Democratic Republic of	1	0	Korea, South	0	1
Congo, Republic of	1	0	Kuwait	0	1
Costa Rica	0	1	Kyrgyz Republic	1	0
Cote d'Ivoire	1	0	Laos	1	0
Croatia	0	1	Latvia	0	1
Cyprus	0	1	Lebanon	0	1
Czech Republic	0	1	Lesotho	1	0
Denmark	0	1	Liberia	1	0
Djibouti	1	0	Libya	0	1
Dominica	0	1	Lithuania	0	1
Dominican Republic	0	1	Macedonia	1	0
Ecuador	0	1	Madagascar	1	0
Egypt	0	1	Malawi	1	0

Table A3: Country Samples, Continued (1980 - 2014)

Country	**CCCs**	**non-CCCs**	**Country**	**CCCs**	**non-CCCs**
Malaysia	0	1	Somalia	1	0
Maldives	1	0	South Africa	0	1
Mali	1	0	Spain	0	1
Malta	0	1	Sri Lanka	0	1
Marshall Islands	0	1	Sudan	1	0
Mauritania	1	0	Suriname	0	1
Mauritius	0	1	Swaziland	1	0
Mexico	0	1	Sweden	0	1
Micronesia, Federated States of	0	1	Switzerland	0	1
Moldova	1	0	Syrian Arab Republic	0	1
Mongolia	1	0	Tajikistan	0	1
Morocco	0	1	Tanzania	1	0
Mozambique	1	0	Thailand	0	1
Myanmar	1	0	Togo	1	0
Namibia	0	1	Tonga	0	1
Nepal	1	0	Trinidad and Tobago	0	1
Netherlands	0	1	Tunisia	0	1
Netherlands Antilles	0	1	Turkey	0	1
New Zealand	0	1	Turkmenistan	1	0
Nicaragua	1	0	Uganda	1	0
Niger	1	0	Ukraine	0	1
Nigeria	0	1	United Arab Emirates	0	1
Norway	0	1	United Kingdom	0	1
Oman	0	1	United States	0	1
Pakistan	0	1	Uruguay	0	1
Panama	0	1	Uzbekistan	1	0
Papua New Guinea	0	1	Vanuatu	1	0
Paraguay	1	0	Venezuela	0	1
Peru	0	1	Viet Nam	0	1
Philippines	0	1	Yemen	1	0
Poland	0	1	Zambia	1	0
Portugal	0	1	Zimbabwe	1	0
Qatar	0	1			
Romania	0	1			
Russia	0	1			
Rwanda	1	0			
Saint Kitts and Nevis	0	1			
Saint Lucia	0	1			
Saint Vincent and the Grenadines	0	1			
Samoa	1	0			
San Marino	0	1			
Sao Tome and Principe	1	0			
Saudi Arabia	0	1			
Senegal	1	0			
Seychelles	0	1			
Sierra Leone	1	0			
Singapore	0	1			
Slovak Republic	0	1			
Slovenia	0	1			
Solomon Islands	1	0			

Table A4: Supply and Demand Effects, Monthly (1980 - 2014)

Dep. Var.:	$\mu_{i,t}$, Supply				$\zeta_{i,t}$, Demand			
Event Type:	Earthquake		Storm		Earthquake		Storm	
Sample:	CCC	non-CCC	CCC	non-CCC	CCC	non-CCC	CCC	non-CCC
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Event (t-1)	−0.1937	−0.0153	−0.2055	−0.0209	−0.0957	0.0644**	0.0583	0.0061
	(0.12)	(0.04)	(0.22)	(0.10)	(0.06)	(0.03)	(0.05)	(0.05)
Event (t)	−0.1684	0.0207	−0.4783***	−0.1130	−0.1805	0.0689***	−0.0589	0.0146
	(0.22)	(0.04)	(0.07)	(0.13)	(0.20)	(0.02)	(0.17)	(0.04)
Event (t+1)	−0.4294*	0.0127	−0.6972***	−0.1113	−0.0235	0.0688***	−0.0738	0.0530
	(0.23)	(0.04)	(0.16)	(0.10)	(0.20)	(0.02)	(0.05)	(0.03)
Event (t+2)	−0.6265***	−0.0180	−0.5175***	−0.1277	0.0166	0.0525**	0.0616	0.0248
	(0.18)	(0.04)	(0.19)	(0.11)	(0.11)	(0.02)	(0.14)	(0.04)
Event (t+3)	−0.2822*	−0.0394	−0.6641***	−0.1819	0.0119	0.0331	0.0042	0.0655
	(0.15)	(0.08)	(0.17)	(0.12)	(0.07)	(0.03)	(0.13)	(0.04)
Event (t+4)	−0.3867**	−0.0013	−0.8061***	−0.1976	−0.0758	0.0541	0.5667***	−0.0116
	(0.16)	(0.05)	(0.20)	(0.13)	(0.09)	(0.03)	(0.12)	(0.05)
Event (t+5)	−0.3509**	−0.0049	−0.3508	−0.1917	−0.0864	0.0761***	0.3281***	0.0995***
	(0.15)	(0.04)	(0.35)	(0.12)	(0.12)	(0.02)	(0.11)	(0.03)
Event (t+6)	−0.4049***	0.0210	−0.8619***	−0.1787	−0.3197*	0.0419*	0.0687	0.0100
	(0.15)	(0.04)	(0.11)	(0.13)	(0.16)	(0.02)	(0.09)	(0.03)
Event (t+7)	−0.3835***	−0.0478	−0.4668***	−0.0317	−0.3242**	0.0443*	0.0350	0.0723***
	(0.13)	(0.06)	(0.14)	(0.08)	(0.16)	(0.02)	(0.11)	(0.02)
Event (t+8)	−0.5596**	−0.0554	−0.3542***	0.0129	−0.1332*	0.0490**	0.0514	0.0643*
	(0.26)	(0.06)	(0.12)	(0.08)	(0.08)	(0.02)	(0.14)	(0.04)
Event (t+9)	−0.4900***	−0.0196	−0.6486***	0.1461	−0.2449**	0.0353**	0.1766	0.1009**
	(0.13)	(0.04)	(0.16)	(0.09)	(0.10)	(0.02)	(0.28)	(0.04)
Event (t+10)	−0.3964***	−0.0558	−0.6579***	0.0463	−0.2287*	0.0453	−0.0437	0.0305
	(0.15)	(0.07)	(0.14)	(0.07)	(0.14)	(0.03)	(0.18)	(0.03)
Event (t+11)	−0.2432	−0.0011	−0.5306***	−0.0608	−0.2338**	0.0420*	−0.0693	0.0352
	(0.17)	(0.03)	(0.14)	(0.09)	(0.11)	(0.02)	(0.08)	(0.03)
Event (t+12)	−0.4814**	0.0225	−0.5777***	−0.1780	−0.1979	0.0519**	−0.1536*	0.0206
	(0.24)	(0.04)	(0.09)	(0.11)	(0.18)	(0.02)	(0.08)	(0.06)
R^2	0.952				0.969			

Notes: ***, **, * denote significance at the 1%, 5%, 10% levels, respectively. All models estimated use a fixed effects (FE) regression with heteroskedasticity robust standard errors clustered at the country level (in parentheses). Time (month-year) and country-month (seasonality) fixed effects and cubic country-specific time trend are included in all specifications but not reported. CCC: Credit-constrained countries. non-CCC: non-credit-constrained countries. Observations: 66,576.

Table A5: Robustness: Supply and Demand Effects, Monthly (1980 - 2014)

Dep. Var.:	$\mu_{i,t}$, Supply				$\zeta_{i,t}$, Demand			
Event Type:	Earthquake		Storm		Earthquake		Storm	
Sample:	CCC	non-CCC	CCC	non-CCC	CCC	non-CCC	CCC	non-CCC
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Linear Country-Specific Time Trend								
Event (t-1)	−0.1877	−0.0138	−0.1777	0.0333	−0.0649	0.0555*	0.0640*	0.0177
	(0.13)	(0.04)	(0.26)	(0.08)	(0.05)	(0.03)	(0.04)	(0.05)
Event (t)	−0.1622	0.0209	−0.4503***	−0.0603	−0.1495	0.0596**	−0.0527	0.0257
	(0.20)	(0.04)	(0.11)	(0.11)	(0.19)	(0.02)	(0.18)	(0.04)
Event (t+1)	−0.4226*	0.0154	−0.6695***	−0.0601	0.0078	0.0606***	−0.0671*	0.0632*
	(0.23)	(0.04)	(0.19)	(0.09)	(0.19)	(0.02)	(0.04)	(0.03)
Event (t+2)	−0.6150***	−0.0158	−0.4892**	−0.0692	0.0484	0.0438*	0.0690	0.0399
	(0.19)	(0.04)	(0.21)	(0.10)	(0.10)	(0.02)	(0.14)	(0.04)
Event (t+3)	−0.2705*	−0.0376	−0.6357***	−0.1223	0.0439	0.0237	0.0122	0.0809**
	(0.16)	(0.08)	(0.18)	(0.11)	(0.07)	(0.03)	(0.12)	(0.03)
Event (t+4)	−0.3756**	0.0006	−0.7775***	−0.1375	−0.0445	0.0447	0.5753***	0.0038
	(0.17)	(0.04)	(0.23)	(0.12)	(0.09)	(0.03)	(0.10)	(0.04)
Event (t+5)	−0.2872**	−0.0032	−0.3221	−0.1437	−0.0366	0.0664***	0.3372***	0.1107***
	(0.13)	(0.04)	(0.36)	(0.10)	(0.11)	(0.02)	(0.11)	(0.03)
Event (t+6)	−0.3413**	0.0227	−0.8331***	−0.1307	−0.2699*	0.0318	0.0783	0.0212
	(0.14)	(0.03)	(0.13)	(0.11)	(0.16)	(0.02)	(0.09)	(0.03)
Event (t+7)	−0.3203**	−0.0463	−0.4380***	0.0163	−0.2743*	0.0335	0.0450	0.0835***
	(0.13)	(0.06)	(0.16)	(0.07)	(0.15)	(0.02)	(0.09)	(0.02)
Event (t+8)	−0.4965*	−0.0541	−0.3254**	0.0600	−0.0834	0.0377*	0.0619	0.0755**
	(0.26)	(0.06)	(0.14)	(0.05)	(0.08)	(0.02)	(0.14)	(0.03)
Event (t+9)	−0.4270***	−0.0180	−0.6197***	0.1914**	−0.1950**	0.0239	0.1876	0.1117***
	(0.13)	(0.04)	(0.17)	(0.08)	(0.09)	(0.02)	(0.26)	(0.04)
Event (t+10)	−0.3336**	−0.0548	−0.6231***	0.0864*	−0.1789	0.0335	−0.0423	0.0413
	(0.13)	(0.06)	(0.16)	(0.05)	(0.13)	(0.03)	(0.17)	(0.03)
Event (t+11)	−0.1805	−0.0008	−0.4955***	−0.0201	−0.1839*	0.0292	−0.0672	0.0462
	(0.15)	(0.02)	(0.16)	(0.07)	(0.10)	(0.02)	(0.08)	(0.03)
Event (t+12)	−0.4190*	0.0226	−0.5429***	−0.1407	−0.1480	0.0384**	−0.1512*	0.0272
	(0.23)	(0.04)	(0.13)	(0.10)	(0.17)	(0.02)	(0.08)	(0.05)
R^2	0.958				0.972			
Panel B: Quadratic Country-Specific Time Trend								
Event (t-1)	−0.1951	−0.0158	−0.2053	0.0007	−0.0809	0.0652**	0.0527	0.0101
	(0.13)	(0.04)	(0.23)	(0.09)	(0.06)	(0.03)	(0.04)	(0.05)
Event (t)	−0.1697	0.0197	−0.4780***	−0.0919	−0.1655	0.0694***	−0.0642	0.0184
	(0.22)	(0.04)	(0.08)	(0.12)	(0.20)	(0.02)	(0.17)	(0.04)
Event (t+1)	−0.4304*	0.0130	−0.6969***	−0.0907	−0.0084	0.0694***	−0.0789*	0.0565*
	(0.24)	(0.04)	(0.17)	(0.10)	(0.20)	(0.02)	(0.05)	(0.03)
Event (t+2)	−0.6268***	−0.0179	−0.5169***	−0.1039	0.0312	0.0529**	0.0569	0.0305
	(0.19)	(0.04)	(0.20)	(0.11)	(0.11)	(0.02)	(0.14)	(0.04)
Event (t+3)	−0.2824*	−0.0395	−0.6634***	−0.1575	0.0266	0.0333	−0.0002	0.0713*
	(0.15)	(0.08)	(0.17)	(0.12)	(0.07)	(0.03)	(0.12)	(0.04)
Event (t+4)	−0.3871**	−0.0013	−0.8053***	−0.1729	−0.0613	0.0542	0.5625***	−0.0059
	(0.16)	(0.05)	(0.21)	(0.13)	(0.09)	(0.03)	(0.11)	(0.05)
Event (t+5)	−0.3286**	−0.0051	−0.3498	−0.1709	−0.0669	0.0759***	0.3242***	0.1040***
	(0.14)	(0.04)	(0.36)	(0.11)	(0.11)	(0.02)	(0.11)	(0.03)
Event (t+6)	−0.3826***	0.0208	−0.8608***	−0.1579	−0.3001*	0.0415*	0.0651	0.0146
	(0.14)	(0.04)	(0.12)	(0.12)	(0.16)	(0.02)	(0.09)	(0.03)
Event (t+7)	−0.3613***	−0.0481	−0.4657***	−0.0108	−0.3045*	0.0436*	0.0315	0.0769***
	(0.13)	(0.06)	(0.15)	(0.08)	(0.16)	(0.02)	(0.10)	(0.02)
Event (t+8)	−0.5374**	−0.0559	−0.3530***	0.0335	−0.1134	0.0482**	0.0482	0.0688**
	(0.26)	(0.06)	(0.13)	(0.06)	(0.08)	(0.02)	(0.14)	(0.03)
Event (t+9)	−0.4677***	−0.0200	−0.6473***	0.1661*	−0.2250**	0.0343**	0.1737	0.1053**
	(0.13)	(0.04)	(0.17)	(0.08)	(0.10)	(0.02)	(0.27)	(0.04)
Event (t+10)	−0.3741***	−0.0564	−0.6532***	0.0643	−0.2087	0.0441	−0.0500	0.0348
	(0.14)	(0.07)	(0.15)	(0.06)	(0.14)	(0.03)	(0.17)	(0.03)
Event (t+11)	−0.2209	−0.0020	−0.5256***	−0.0424	−0.2137**	0.0404*	−0.0754	0.0395
	(0.16)	(0.02)	(0.15)	(0.08)	(0.11)	(0.02)	(0.08)	(0.03)
Event (t+12)	−0.4591*	0.0214	−0.5728***	−0.1610	−0.1777	0.0500***	−0.1595**	0.0235
	(0.23)	(0.04)	(0.10)	(0.11)	(0.18)	(0.02)	(0.08)	(0.05)
R^2	0.955				0.971			

Notes: ***, **, * denote significance at the 1%, 5%, 10% levels, respectively. All models estimated use a fixed effects (FE) regression with heteroskedasticity robust standard errors clustered at the country level (in parentheses). Time (month-year) and country-month (seasonality) fixed effects and country-specific time trend are included in all specifications but not reported. CCC: Credit-constrained countries. non-CCC: non-credit-constrained countries. Observations: 66,576.

Table A6: Specific Events, Homogeneous Effect within Quarter (1980 - 2014)

Dep. Var.:	$\mu_{i,t}$, Supply		$\zeta_{i,t}$, Demand	
Disaster Event:	Earthquake	Tohoku Earthquake	Earthquake	Tohoku Earthquake
Country:	Nicaragua	Japan	Nicaragua	Japan
Month/Year (t)	09/1992	3/2011	09/1992	3/2011
Event (t-3)	−0.0301	0.0208	−0.0409	−0.0040
	(0.04)	(0.03)	(0.03)	(0.02)
Event (t)	−0.4678***	−0.1013***	−0.2287***	−0.0260
	(0.04)	(0.03)	(0.03)	(0.02)
Event (t-+3)	−0.6124***	−0.1660***	−0.1184***	0.0129
	(0.04)	(0.03)	(0.02)	(0.02)
Event (t+6)	−0.0616	−0.0269	−0.2536***	0.0360*
	(0.05)	(0.03)	(0.02)	(0.02)
Event (t+9)	−0.2884***	−0.0301	−0.4703***	0.0164
	(0.04)	(0.03)	(0.02)	(0.02)
Event (t+12)	−0.1590***	−0.0336	−0.0987***	0.1398***
	(0.04)	(0.04)	(0.03)	(0.02)
Event (t+15)	−0.2745***	−0.0183	−0.3002***	0.0873***
	(0.04)	(0.04)	(0.03)	(0.02)
Event (t+18)	0.0033	0.0176	−0.3671***	0.1202***
	(0.03)	(0.03)	(0.03)	(0.02)
Event (t+21)	−0.0944**	−0.0801***	−0.2415***	0.0816***
	(0.04)	(0.03)	(0.03)	(0.02)
Event (t+24)	−0.2475***	−0.1321***	−0.1999***	0.0937***
	(0.04)	(0.03)	(0.03)	(0.02)

Notes: ***, **, * denote significance at the 1%, 5%, 10% levels, respectively. All models estimated use a fixed effects (FE) regression with heteroskedasticity robust standard errors clustered at the country level (in parentheses). Time (month-year) and country-month (seasonality) fixed effects and cubic country specific time trend are included in all specifications but not reported. Three-monthly (quarterly) lead and 24 monthly lags included. Control events include earthquakes in Nicaragua and Japan above a magnitude of six Richter and within the top five percent of earthquakes within the observed time frame. Observations: 64,774. R^2 is 0.953 for supply and 0.971 for demand.

Table A7: Specific Events, Monthly (1980 - 2014)

Dep. Var.:	$\mu_{i,t}$, Supply		$\zeta_{i,t}$, Demand	
Disaster Event:	Earthquake	Tohoku Earthquake	Earthquake	Tohoku Earthquake
Country:	Nicaragua	Japan	Nicaragua	Japan
Month/Year (t)	09/1992	3/2011	09/1992	3/2011
Event (t-1)	−0.3674***	0.0303	−0.1109***	0.0738***
	(0.04)	(0.03)	(0.03)	(0.02)
Event (t)	−0.5192***	−0.1034***	−0.2245***	−0.0383*
	(0.03)	(0.03)	(0.03)	(0.02)
Event (t+1)	−0.8525***	−0.1138***	−0.0152	−0.0066
	(0.04)	(0.03)	(0.02)	(0.02)
Event (t+2)	−0.6594***	−0.2769***	−0.1425***	−0.0332
	(0.05)	(0.03)	(0.03)	(0.02)
Event (t+3)	−0.4788***	−0.0809**	−0.1851***	−0.0175
	(0.04)	(0.03)	(0.02)	(0.02)
Event (t+4)	−0.3738***	0.0230	−0.0583**	0.0149
	(0.05)	(0.03)	(0.03)	(0.02)
Event (t+5)	−0.1728***	−0.1002***	−0.0271	−0.0190
	(0.04)	(0.03)	(0.03)	(0.02)
Event (t+6)	0.2802***	0.0443	−0.5546***	0.0396
	(0.05)	(0.03)	(0.03)	(0.03)
Event (t+7)	−0.1991***	−0.0411	−0.5123***	0.0082
	(0.04)	(0.03)	(0.03)	(0.02)
Event (t+8)	−0.2988***	−0.0730**	−0.3720***	0.0490**
	(0.04)	(0.04)	(0.03)	(0.02)
Event (t+9)	−0.5322***	0.0704*	−0.4133***	−0.0006
	(0.04)	(0.04)	(0.03)	(0.02)
Event (t+10)	−0.2094***	−0.0971**	−0.1507***	0.1685***
	(0.04)	(0.04)	(0.03)	(0.02)
Event (t+11)	−0.1283***	0.0510	−0.0745**	0.1457***
	(0.04)	(0.04)	(0.03)	(0.02)
Event (t+12)	−0.3181***	−0.0350	0.0449	0.0970***
	(0.04)	(0.03)	(0.03)	(0.02)

Notes: ***, **, * denote significance at the 1%, 5%, 10% levels, respectively. All models estimated use a fixed effects (FE) regression with heteroskedasticity robust standard errors clustered at the country level (in parentheses). Time (month-year) and country-month (seasonality) fixed effects and cubic country specific time trend are included in all specifications but not reported. Control events include earthquakes in Nicaragua and Japan above a magnitude of six Richter and within the top five percent of earthquakes within the observed time frame. Observations: 66,576. R^2 is 0.952 for supply and 0.969 for demand.

Table A8: Model-implied Annualized Welfare Effects: Impact of Trade Costs for 03/2011 Tohoku Earthquake, Japan

Event:	Tohoku Earthquake, Japan					
	estimated trade costs			no trade costs		
	only supply $\Delta A_{i,t}$	only demand $\Delta d_{i,t}$	supply & demand $\Delta A_{i,t}$ & $\Delta d_{i,t}$	only supply $\Delta A_{i,t}$	only demand $\Delta d_{i,t}$	supply & demand $\Delta A_{i,t}$ & $\Delta d_{i,t}$
Per Period Welfare Effect for Japan						
t	-0.8	-0.4	-1.1	-0.4	-0.2	-0.7
$t+3$	-1.2	0.2	-1.1	-0.7	0.1	-0.6
$t+6$	-0.2	0.6	0.3	-0.1	0.3	0.2
$t+9$	-0.2	0.3	0.0	-0.1	0.1	0.0
$t+12$	-0.3	2.3	2.0	-0.2	1.3	1.1
$t+24$	-1.0	1.5	0.3	-0.6	0.8	0.2
Indirect Welfare Effect on Rest of the World (Median)						
t	-0.0	-0.0	-0.0	-0.0	-0.0	-0.1
$t+3$	-0.0	0.0	-0.0	-0.1	0.0	-0.1
$t+6$	-0.0	0.0	0.0	-0.0	0.0	0.0
$t+9$	-0.0	0.0	-0.0	-0.0	0.0	0.0
$t+12$	-0.0	0.1	0.1	-0.0	0.1	0.1
$t+24$	-0.0	0.1	0.0	-0.1	0.1	0.0

Notes: Table reports model-implied annualized welfare effects in percent, where welfare is measured as monthly real income. t is the month of the disaster event. Annualized effects calculated as 1/12 of the monthly effects reported in Table 2.

Table A9: Model-implied Annualized Welfare Effects: Impact of Trade Costs for 09/1992 Earthquake, Nicaragua

Event:	**Earthquake, Nicaragua**					
	estimated trade costs			no trade costs		
	only supply $\Delta A_{i,t}$	only demand $\Delta d_{i,t}$	supply & demand $\Delta A_{i,t}$ & $\Delta d_{i,t}$	only supply $\Delta A_{i,t}$	only demand $\Delta d_{i,t}$	supply & demand $\Delta A_{i,t}$ & $\Delta d_{i,t}$
Per Period Welfare Effect for Nicaragua						
t	-1.6	-0.7	-2.2	-1.8	-0.7	-2.3
$t+3$	-2.1	-0.4	-2.3	-2.3	-0.4	-2.5
$t+6$	-0.2	-0.8	-1.0	-0.2	-0.8	-1.0
$t+9$	-1.0	-1.4	-2.2	-1.1	-1.4	-2.3
$t+12$	-0.6	-0.3	-0.8	-0.6	-0.3	-0.9
$t+24$	-0.9	-0.6	-1.4	-1.0	-0.6	-1.5
Indirect Welfare Effect on Rest of the World (Median)						
t	-0.0	-0.0	-0.0	-0.0	-0.0	-0.0
$t+3$	-0.0	-0.0	-0.0	-0.0	-0.0	-0.0
$t+6$	-0.0	-0.0	-0.0	-0.0	-0.0	-0.0
$t+9$	-0.0	-0.0	-0.0	-0.0	-0.0	-0.0
$t+12$	-0.0	-0.0	-0.0	-0.0	-0.0	-0.0
$t+24$	-0.0	-0.0	-0.0	-0.0	-0.0	-0.0

Notes: Table reports model-implied annualized welfare effects in percent, where welfare is measured as monthly real income. t is the month of the disaster event. Annualized effects calculated as 1/12 of the monthly effects reported in Table 3.