Quantifying the Demand, Supply, and Welfare Effects of Natural Disasters Using Monthly Trade Data[◇]

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We estimate the short-run trade effects of natural disasters using monthly trade data and data on the physical intensity of earthquakes and storms. We find large negative effects for heavily indebted poor, least developed or landlocked developing countries but only small effects for other economies. We use our estimates to identify key parameters of a dynamic quantitative trade model to disentangle the effects of disasters on supply, demand, and welfare and their spillovers on third countries via trade linkages. We apply our model to quantify the effects of the 1992 earthquake in Nicaragua, a small, heavily indebted poor country, and the 2011 Tohoku earthquake in Japan, a large developed economy. We find that spillovers are negligible if the country affected by a disaster is small but sizable for large economies. Similar disasters have heterogeneous effects on countries' demand and supply, highlighting the importance of event-specific policies in the aftermath of disasters.

JEL Classification Codes: F14; F18; Q54; C68

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

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1 Introduction

Natural disasters affect the livelihood of millions and wreak large economic damages. As the occurrence of natural disasters cannot directly be controlled by humans, adaption is a pressing issue. To do so successfully policy makers and the private sector need a clear understanding of the economic consequences of such events. However, while there exists a burgeoning literature on the physical effects of natural disasters and how their occurrence will be affected by climate change, the study of the economic consequences of natural disasters is underdeveloped.[1] The literature has mostly focused on the long-run economic consequences of disasters by quantifying their effect on annual 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). One reason for these mixed results may be that aggregate annual GDP, the measure used to gauge disasters' impact in these studies, is too coarse a measure: Disasters may have large but opposing effects on aggregate supply and demand via their productivity and expenditure effects. This makes disentangling their effects from aggregate GDP data difficult as the destruction of physical infrastructure and capital caused by such events reduces a country's productivity, but its expenditure may actually increase due to the heightened replacement activity in the aftermath of the disaster.

Annual GDP data may also be too coarse to capture the short-run impact of disasters, as physical damage of disasters occurs very quickly: Disasters like storms can wreak havoc to communities within hours or, in the case of earthquakes, even minutes. Similarly, while disaster relief efforts may not react fast enough to prevent damages and loss of lives, their reaction time is typically not measured in years. More to the point, firms react quickly with their reconstruction efforts. 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 recover quickly from such an idiosyncratic shock 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. Annual data will therefore likely underestimate the size of the adjustment process in economic activity after a natural disaster. To this date, there is no study which quantifies the short-run effects of natural disasters for a large set of countries.

In this paper, we use monthly international trade to overcome both shortcomings in the literature. They allow us to identify the potential short-run effects of natural disasters and to disentangle the

[1] For overviews of this literature see Cavallo and Noy (2011) and Auffhammer (2018).

potentially opposing supply and demand effects. Monthly data also solve the common problem that annual data can hardly allow for a differential impact of a natural disaster shock occurring at the beginning versus at the end of the calendar year without arbitrary assumptions about apportioning annual damages across months. Trade data are available at a monthly frequency for many countries, including developing and least developed countries, allowing a much more detailed view on the economic effects of natural disasters compared to annual GDP data. Also, trade is particularly vulnerable to natural disasters. On the supply side, disasters can destroy public and private assets (e.g., power plants, factories) which are crucial for production, hence lowering the productivity in the economy, reducing its exports. Also, established trading relationships may be disrupted by natural disasters, affecting supply chains for intermediate inputs. On the demand side, the destruction of assets acts like a negative income shock, reducing domestic expenditure and hence imports. At the same time, countries may increase their imports in the short-run to replace destroyed capital and infrastructure. In addition, firms may have to source inputs from foreign suppliers to make up for wiped out domestic suppliers, increasing imports. This may be difficult for developing countries with high debt levels as they may not be able to finance this additional expenditure. It is not clear whether the shocks to supply or demand are empirically more important: Do idiosyncratic disaster shocks predominantly affect a country's export supply via its impact on infrastructure and capital stocks, and ultimately, productivity, or do they predominantly act as an expenditure shock? And how long do these effects persist? Trade data allow us to answer all these questions. We use a panel of monthly merchandize trade data for 180 countries from 1980 to 2014 which allow us for the first time to estimate the causal effect of disasters on both a country's exports and imports in the short-run. Using a quantitative trade model, we show how these effects can be disentangled into their supply and demand effects. As we focus on short-term effects, we concentrate on two short-lived disasters: earthquakes and storms.[2]

Besides its reliance on annual data, the literature typically uses economic damage data to measure the severity of a natural disaster. These data have been shown to contain reporting issues (Strobl, 2012; Felbermayr and Gröschl, 2014). As these data are based on the outcome of the disaster, they also create endogeneity problems: 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). We therefore use the gridded GAME data of geological and meteorological events collected by Felbermayr et al. (2018). This data set combines physical intensities for various kinds of natural disasters that are collected from primary sources, covering the entire globe at a 0.5 degree grid-cell level from 1980 to 2014.

[2]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).

Identifying the demand and supply effects of disasters from our trade data necessitates a structural model. State-of-the-art quantitative trade models are static models, see the survey by Head and Mayer (2014). Hence, they do not address the dynamic short-run adjustments of trade flows as they do not model inter temporal consumption smoothing behavior of consumers via borrowing or lending.[3] We therefore develop a simple dynamic extension of standard quantitative trade models. The advantage of our model is foremost its simplicity: It can be calibrated using only monthly trade data, annual GDP per capita data and readily available country-level trade cost measures. While its stylized nature obviously falls short of the complexity of the real world, it still captures the essence of dynamic adjustments in trade flows and provides a consistent framework to identify the demand, supply and welfare effects of natural disasters. Crucially, its simplicity means that it can also be applied to least developed countries where more detailed production data are not available. Also, while being dynamically consistent, conditional on monthly supply and demand effects identified from the data, it can be solved as a sequence of static problems, simplifying its implementation for the large set of countries we study. Importantly, its general equilibrium nature allows us to quantify the potential spillover effects of disaster shocks and how trade costs and countries' economic size shape the distribution of these spillovers. It also allows us to separate the aggregate disaster effect into the supply and demand channels. We can then calculate the monthly welfare effects (in terms of real income) of the disasters and gauge the relative importance of the channels.

As a byproduct of our quantitative trade model, we provide a monthly country-specific measure for economic activity as proxied by our calibrated country-specific monthly productivity measures. While not perfect, our measure correlates reasonably well with economic events and published TFP measures which are derived from more detailed data on output and production factor use, which are not always available and typically are measured at the quarterly level only. Importantly, our measure can be easily calculated for a large panel of countries as it can be derived using only bilateral trade data.

Our results show that the same type of disaster has different effects, depending on a country's level of development and indebtedness: Least developed countries and poor countries with high external debt levels have difficulties of accessing financial markets to fund potential increases in public and private expenditure after a disaster. Also, international disaster relief aid only covers about three percent of estimated economic damages (see Becerra et al., 2014). As a result, developing countries tend to exacerbate the effects of disasters by adopting pro-cyclical fiscal policies (see Noy and Nualsri, 2011). Our findings support this: We do not find statistically

[3] Alvarez (2017), Anderson et al. (2015), 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 idiosyncratic 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.

significant effects of earthquakes on neither export supply nor import demand for developed countries. Storms also do not have significant effects on developed countries' export supply. We do find small positive effects of storms on developed countries' import demand, in line with consumption smoothing, as developed countries can access financial markets to finance an increase in demand.

Results are different for least developed, landlocked developing and heavily indebted poor countries: Earthquakes reduce export supply by about 20% in the month of the disaster, but recovers within half a year. Import demand reductions last up to eleven month after the earthquake struck, with losses of 4 to 20 percent. Storms have even larger effects on these countries: export supply drops consistently for twelve months, with a reduction of 48 percent in the month of the storm. Interestingly, we do not find a significant decrease in demand.

To investigate the potential differences in how economies react to similar disasters, we then use our estimated export and supply effects to inform the parameters of our quantitative trade model and apply it to two particularly devastating earthquakes: The 1992 earthquake in Nicaragua, a heavily indebted poor country, and the 2011 Tohoku earthquake in Japan, a developed economy.

Our model simulations find that the 1992 earthquake in Nicaragua lead to an immediate reduction in monthly real incomes, our measure of welfare, of -19.3 percent, mostly driven by a large negative supply shock (-14.2 percent), in addition to a fall in monthly demand by -6.0 percent. These effects remain negative 24 months after the earthquake. In Japan, immediate effects on monthly real incomes are even larger (-23.3 percent), but monthly demand is larger 12 and 24 months after the earthquake. Overall, results are heterogeneous, both in terms of magnitude and dynamics, highlighting the importance of taking into account the individual situation of affected countries at the moment of the disaster. Our findings may therefore also explain conflicting evidence in the literature. Finally, 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 smaller or poorer economies like Nicaragua hardly affect outcomes in other countries.

Our results have important policy implications. Observed reductions in supply like after the earthquake in Nicaragua in 1992 and hence large negative real income effects implied by our model may be due to a lack of access to international capital markets for poorer, more remote countries or those with already high external debt levels. This highlights the importance of offering financial disaster relief by facilitating lending, both for the private and public sector, in order to facilitate optimal consumption smoothing and rebuilding activities of affected countries. The heterogeneity of our results also stresses the importance of taking into account the characteristics of affected countries instead of applying one-size-fits-all relief policies. Our results also highlight that 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. investigates the annual growth impact of disasters in a panel of countries but his measure of 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); Saito et al. (2016); Boehm et al. (2019a) study the disruptive effects of the Great East Japan Earthquake on supply chains of Japanese firms. Barrot and Sauvagnat (2016) study whether firm-level shocks propagate in production networks considering major natural disasters in the past 30 years in the United States. These events have large quarterly effects on the sales growth of affected firms. We contribute to this literature by providing the first estimates of the monthly trade effects of disasters, and by quantifying the international spillover effects of these disasters using a dynamic quantitative trade model.

We also relate to an emerging literature which uses exogenous data on physical natural disaster intensities (Hallegatte et al., 2010; Hsiang, 2010; Strobl, 2011; Burke et al., 2015), albeit without focusing on trade as we do. Closest to our paper is the literature which studies the effects of disasters on annual trade flows: Gassebner et al. (2010) and Oh and Reuveny (2010) use annual bilateral trade flows to assess the impact of disasters on international trade. They find that international trade allows countries to smooth out the effects of temporary output shocks. Felbermayr and Gröschl (2013) show that large disasters increase imports of an affected country. Compared to these papers, our quantitative trade model allows us to identify the monthly supply and demand effects of disasters.

The remainder of the paper is structured as follows. Section 2 presents a simple dynamic general equilibrium quantitative trade model from which we derive estimable equations. Section 3 describes the empirical implementation and Section 4 the trade and disaster data. Section 5 presents our estimates of the trade effects of disasters. Section 6 shows how the estimated trade effects can be used in our general equilibrium model to quantify the per period demand, supply, welfare and spillover effects of disasters. Section 7 concludes.

2 A Simple Dynamic Model for Trade Flows and Disasters

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

$$U_{j,t} = \sum_{t=0}^{\infty} \beta^t u_{j,t}, \tag{1}$$

where per period utility $u_{j,t}$ is derived from consuming varieties which are differentiated by origin country as in Armington (1969):

$$u_{j,t} = \left(\sum_{i=1}^{N} a_i^{\frac{1-\sigma}{\sigma}} q_{ij,t}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}, \tag{2}$$

where $q_{ij,t}$ is the amount of goods from country i country j consumes from i in period t. a_i is a preference parameter which measures the overall attractiveness of a good from a particular country. The consumer maximizes life-time utility $U_{j,t}$ subject to her budget constraint:

$$\begin{aligned} \underbrace{p_{ji,t} s_{ji,t}}_{(I)} + \mathcal{I}(j \text{ can borrow}) \left(\underbrace{\sum_{\tilde{t}=1}^{\infty} \left(\frac{1}{1+r} \right)^{\tilde{t}} \sum_{i=1}^{N} p_{ji,\tilde{t}} s_{ji,\tilde{t}}}_{(II)} + \underbrace{(1+r) B_{j,t}}_{(III)} \right) &= \\ \underbrace{p_{ij,t} q_{ij,t}}_{(IV)} + \mathcal{I}(j \text{ can borrow}) \left(\underbrace{\sum_{\tilde{t}=1}^{\infty} \left(\frac{1}{1+r} \right)^{\tilde{t}} \sum_{i=1}^{N} p_{ij,\tilde{t}} q_{ij,\tilde{t}}}_{(V)} \right)&, \end{aligned} \tag{3}$$

where the left hand side of Equation (3) 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 developed country which can borrow in international financial markets, $\mathcal{I}(j \text{ can borrow}) = 1$, and ii) a developing country which cannot, $\mathcal{I}(j \text{ can borrow}) = 0$. The developed economy can optimize its consumption over time, whereas the developing 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 developed 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 developing 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 (3) reveals that

$$q_{ij,t} = a_i^{1-\sigma} P_{j,t}^{\sigma-1} p_{ij,t}^{-\sigma} E_{j,t}, \tag{4}$$

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

$$P_{j,t} = \left[\sum_{i=1}^{N} (a_i p_{ij,t})^{1-\sigma} \right]^{\frac{1}{1-\sigma}}. \tag{5}$$

Firms produce varieties under constant returns to scale and perfect competition at unit cost $c_{i,t}$. As evidenced by Boehm et al. (2019b), 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

$$p_{i,t} = c_{i,t} = \frac{1}{A_{i,t}} w_{i,t}^{\beta} P_{i,t}^{1-\beta}, \tag{6}$$

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

$$X_{ij,t} = \left(\frac{a_i \tau_{ij,t} c_{i,t}}{P_{j,t}}\right)^{1-\sigma} E_{j,t}, \tag{7}$$

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

Taking logs of Equation (7), we can write

$$\ln X_{ij,t} = \underbrace{(1-\sigma)\ln(a_i c_{i,t})}_{\mu_{i,t},\text{ supply}} + \underbrace{\ln\left(\frac{E_{j,t}}{P_{j,t}^{1-\sigma}}\right)}_{\zeta_{j,t},\text{ demand}} + \underbrace{(1-\sigma)\ln\tau_{ij,t}}_{\text{bilateral trade costs}}. \tag{8}$$

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 (8) 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 in the next Section.

3 Empirical Strategy

3.1 Estimating the Supply and Demand Parameters

To identify the supply and demand parameters, we use state-of-the art best practice to estimate Equation (8) using a Poisson Pseudo-Maximum-Likelihood (PPML) estimator. PPML has been shown to be the only estimator which is 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 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.[4] As we use PPML, we estimate

[4]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. An alternative approach to identify country-specific variables proposed by Heid et al. (2020) relies on domestic production and trade data which are not available for the monthly trade data that we use.

Equation (8) in levels:

$$X_{ij,t} = \exp(\mu_{i,t} + \zeta_{j,t} + \mathbf{x}'_{ij,t}\boldsymbol{\beta} + \xi_{ij} + \varepsilon_{ij,t}), \tag{9}$$

where we have specified the bilateral trade cost term $\tau_{ij,t}$ by a linear combination of observable trade cost drivers, $\mathbf{x}'_{ij,t}\boldsymbol{\beta}$, as well as a directional bilateral fixed effect, ξ_{ij}, and a well-behaved error term, $\varepsilon_{ij,t}$. $\mu_{i,t}$ and $\zeta_{j,t}$ are exporter×month and importer×month fixed effects which capture the supply and demand side components of Equation (8), including the effects of natural disasters.

Table 1: Gravity Estimation: Bilateral Trade Costs, Monthly (1980 - 2014)

Dep. var.:	Imports (1)
ln Distance	-0.779^{***}
	(0.00)
Common border	0.577^{***}
	(0.00)
RTA	0.408^{***}
	(0.00)
GSP	0.082^{***}
	(0.00)
R^2	0.891
Observations	6,044,236

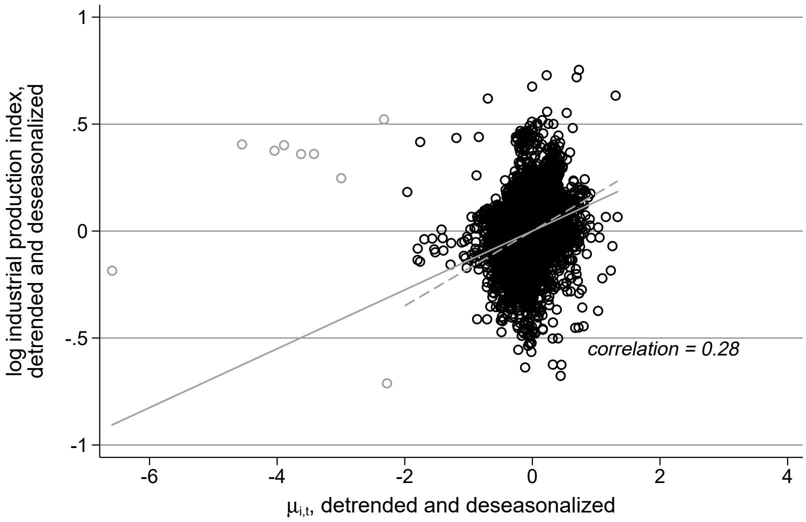
Notes: ***, **, * denote significance at the 1%, 5%, 10% levels, respectively. Estimated with PPML heteroskedasticity robust standard errors. All estimations include importer-time (month-year) and exporter-time fixed effects.

We present coefficient estimates in Table 1. We find the usual size of gravity estimates for the effects of distance, common border, regional trade agreements (RTA) and the generalized system of preferences (GSP).

3.2 Validation

While gravity models like Equation (8) 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.

Figure 1: Correlation of Estimated Supply Parameters with Observed Industrial Production



Notes: Figure shows the scatterplot and fitted regression line between the estimated monthly supply parameters, $\mu_{i,t}$, and the observed (log) monthly industrial production index from the IMF's International Financial Statistics from January 1980 to December 2014. We detrend and deseasonalize the (log) series by regressing on country-specific time trends (including country-specific constants) and country-specific monthly dummies and using the residuals from these regressions. The grey line depicts the predictions of a linear regression between the two series using all observations. The dashed grey line depicts the predictions of a linear regression which excludes nine outliers (marked in by grey circles) for which $\mu_{i,t}$<-2. The correlation between the two series excluding the outliers is 0.32. The outliers are 2011/4 for Côte d'Ivoire, 1997/1 for Luxembourg, and 1992/1,4,6-10 for Kyrgyz Republic.

If $\mu_{i,t}$ captures salient feature's of the variation in countries' aggregate supply, it 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.[5] To avoid a spurious correlation problem as both the (log) industrial production index as well as our estimated productivity series trend upwards over time and exhibit seasonality, we detrend and deseasonalize both series by regressing them on country-specific intercepts, country-specific linear trends, and country-specific month dummies. This also controls for the country-specific base years used in the index data. We then use the residual from these regressions as the detrended and deseasonalized series. We present a scatterplot of the two series in Figure 1. The correlation between our estimated monthly productivity measures and the industrial production index is 0.28, indicating that our supply measures capture a significant part of the variation in industrial production changes.[6]

Table 2 regresses the log industrial production index on the estimated supply parameters and on different sets of fixed effects. Irrespective of the set of fixed effects, our supply measures

[5] We use the "Economic Activity, Industrial Production, Index (AIP_IX)" series from January 1980 to December 2014 for all available countries in our dataset.

[6] In Figure A1 in the Appendix, we show the correlation between industrial production and the estimated productivity parameters without detrending and deseasonalization. Not surprisingly, the correlation (0.67) is higher.

Table 2: Predicting Industrial Production Indices by Estimated Supply Parameters

	(1)	(2)	(3)
Dep. Var.: $\ln(IPIndex_{i,t})$	industrial production		
$\mu_{i,t}$	0.536***	0.214***	0.173**
	(0.067)	(0.057)	(0.055)
R^2 (overall)	0.75	0.92	0.94
R^2 (within)	0.58	0.12	0.10
N	17206	17206	17206
country FEs	X	X	X
country-specific trend		X	X
country-specific month FEs			X

Notes: *** denotes significance at the 1%, 5% level, respectively. Standard errors are clustered at the country level (in parentheses). Time period: Unbalanced panel from January 1980 to December 2014. Note that in column (3), adding country-specific month FEs is tantamount to also controlling for country FEs.

significantly correlate with industrial production (columns (1) to (3)).[7] Our supply measures predict a significant amount of even the within variation, i.e., excluding the variation explained by the country fixed effects, trends, and country-specific seasonality. Note, however, that for predictive purposes, the overall R^2 is more important, as we want our productivity measures to follow the trend and seasonal components closely. In sum, our estimated supply parameters correlate well with observed monthly fluctuations in industrial production, both across countries and across time, validating their use for our counterfactual simulations.

3.3 Estimating Disaster Effects on Demand and Supply

Armed with our demand and supply parameter estimates we can identify how both sides of the economy are affected by disasters in the short-run. We focus on two types of disasters which are of a particularly short-lived nature: earthquakes and storms. We specify the following regressions:

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

[7]Note that one might expect that column (3) produces the same within R^2 and hence correlation as the scatterplot presented in Figure 1 due to the Frisch-Waugh-Lovell theorem. The Frisch-Waugh-Lovell theorem only applies if all regressions are run on the same number of observations. To create the scatterplot, we first detrend the series individually, i.e., we include observations where the other series has missing values, whereas in column (3), we can only run the regression for those observations where we observe both the industrial production index and the estimated productivities. This difference in samples explains the seeming discrepancy between the correlation reported in Figure 1 and the within R^2 in column (3) in Table 2.

$$\begin{aligned}\zeta_{i,t} &= \sum_{k=0}^{K} \beta_k \mathcal{I}(i \text{ can borrow}) \times D_{i,t-k} + \sum_{k=0}^{K} \beta_k^* [1 - \mathcal{I}(i \text{ can borrow})] \times D_{i,t-k} + \\ &+ \rho_{i,m} + \delta_i f(t) + \eta_t + \varepsilon_{i,t} \end{aligned} \quad (10)$$

where $\mu_{i,t}$ and $\zeta_{i,t}$ are our estimated monthly supply and demand parameters from Equation (9) 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 (9), $\ln(\exp(\mu_{i,t})) = \mu_{i,t}$ 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 country which can borrow, α_k^* in a country that cannot borrow, and similarly for the other estimated parameters.

A common problem of many studies of the economic consequences of disasters is that disasters are typically measured by their costs. As costs depend on the economic choices of individuals who may take up extra insurance in disaster-prone countries, cost measures are endogenous. Using physical disaster intensities circumvents this reverse causality problem. Disasters are measured by an indicator variable that takes a value of one if a specific disaster lies above a threshold of Richter five for earthquakes, or above the category one of the Saffir-Simpson Hurricane Wind Scale, i.e., we focus only on major events. In line with our theoretical model, in our regressions we allow for potentially distinct disaster effects α_k and β_k depending on whether a country is able to borrow or not.

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 trade flows tend to increase one to one with income, see

Head and Mayer (2014). As income growth rates differ across countries, we allow for country-specific growth rates in trade flows by including country-specific cubic time trends $\delta_i f(t)$.[8] 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 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 420 months (35 years $\times$ 12 = 420 observations), which is constrained to be identical across all countries.

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.

4 Data

Trade Data. International trade data on monthly bilateral merchandise trade flows come from the IMF's Direction of Trade Statistics (DoTS). The data capture trade between 180 countries from 1980 to 2014, but the panel is unbalanced.[9] The geographical and historical variables capturing trade costs are from CEPII, see Mayer and Zignago (2011). Information on regional trade agreements stem 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 Baier and Bergstrand, available at `http://www.nd.edu/jbergstr/`, first used in Baier et al. (2014). We update this information using primary sources from the WTO, available at `http://ptadb.wto.org/ptaList.aspx`.

Disaster Database. We use the improved version of the Geological and Meteorological Events Database based on Felbermayr and Gröschl (2014), called the gridded GAME database from Felbermayr et al. (2018).[10] It contains physical intensities of natural disasters such as earthquakes, volcanic eruptions, storms, droughts, excessive precipitation and temperature anomalies of 0.5×0.5 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 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 the calculate a population-weighted arithmetic

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

[9] 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.

[10] For a detailed description of the improved database, its primary data sources, and the spatio-temporal aggregation procedures used see Felbermayr et al. (2018).

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.

Earthquakes. We measure earthquakes by their physical magnitude from the Incorporated Research Institutions for Seismology (IRIS). 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 grid-population-weighted earthquake magnitude is distributed between 0 and 7.7. 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 – Richter scale five or higher, and zero otherwise.[12]

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 or 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 65 up to 117.7 knots. In our baseline regression, we translate disaster intensities into treatment dummies taking the value one if a storm has a higher intensity than the Saffir-Simpson hurricane wind scale of 65 kt (category 1 or higher), and zero otherwise.

This means our treatment definition identifies the effects of major earthquakes and storms in

[11] UPSeis is a program and educational site created by the Michigan Technological University for budding seismologists and to teach people 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.

terms of their intensity. Summary statistics of our treatment variables can be found in Table A1 in the Appendix.

Credit-Constrained Country Measure. As the empirical counterpart to $\mathcal{I}(j \text{ can borrow})$, 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 110 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.

5 Results

5.1 Supply and Demand Effects of Disasters

To identify the effects of major earthquakes and storms on countries' export supply and import 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 economies (non-CCCs) to allow for separate disaster effects across the two groups.

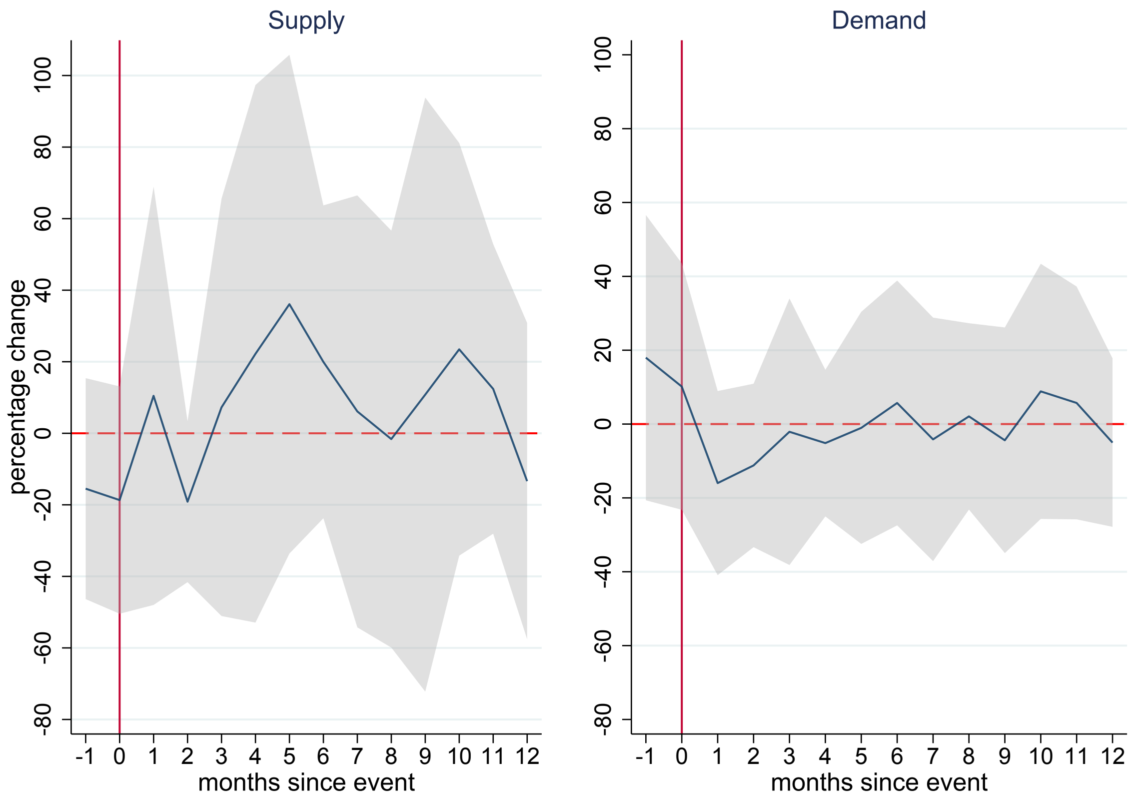
Baseline Results. We display the estimated percentage effects of earthquakes in non-credit-constrained countries in Figure 2 and of storms in Figure 3, and similarly for credit-constrained countries in Figures 4 and 5. We present the underlying regression coefficients in Table A4 in the Appendix. Across 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.

Earthquakes do not significantly affect supply or demand in non-credit-constrained countries. Similarly, export supply shows no statistically significant effect of storms neither for non-credit-constrained countries. We find some significant and positive import demand effects of storms in

[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`.

Figure 2: Effects of Major Earthquakes in Non-Credit-Constrained Countries, in Percent



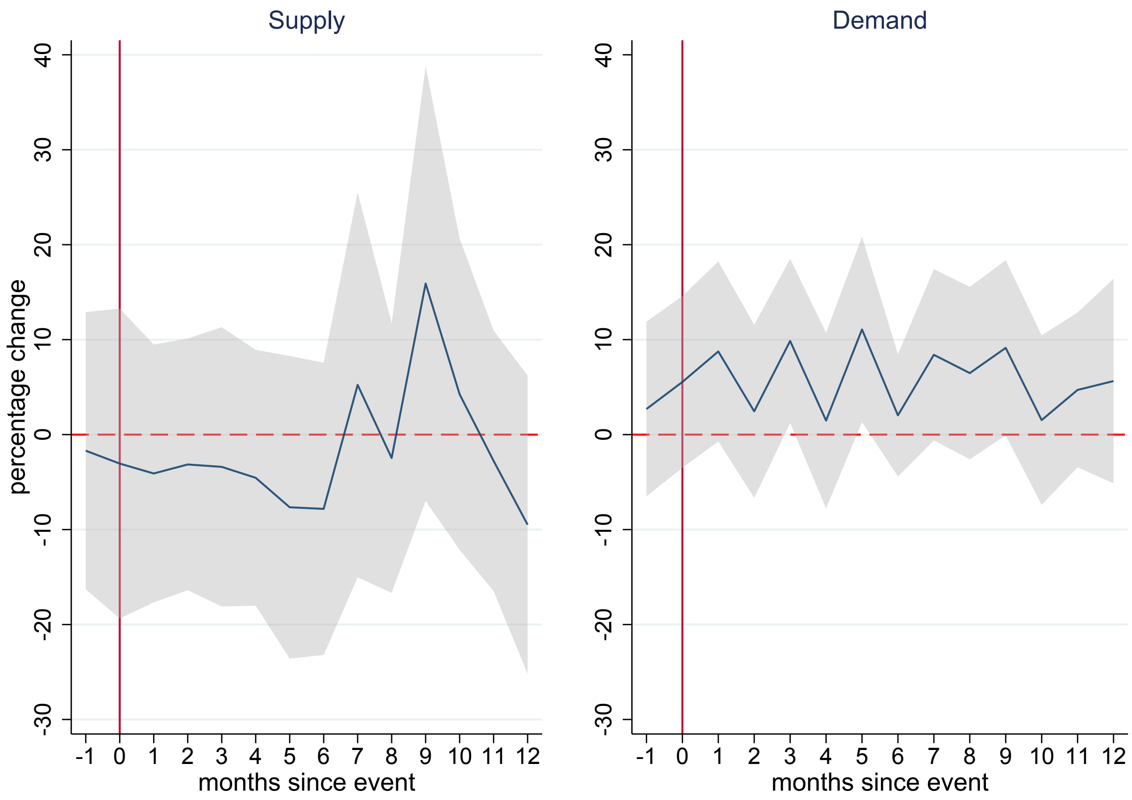
Notes: Figures show estimated percentage change effects of earthquakes on monthly supply and demand. Percentage changes are calculated as $(\exp(\beta_k) - 1) \times 100$. 95% confidence intervals are calculated using the delta method. Estimates and confidence bands are taken from Table A4 columns (2)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

non-CCC countries, but not in every month, consistent with an increase in imports to rebuild destroyed infrastructure and to replace destroyed capital stocks.

Credit-constrained countries are not as lucky: Export supply of CCCs is reduced both by earthquakes and storms. Figure 4 shows that effects of major earthquakes on CCC supply last up to about half a year. CCC supply drops on average by 20 percent in the month of the earthquake. Negative effects are strongest in the second and third month after the earthquake with a reduction in CCC supply of up to 34 percent. Thereafter, supply recovers within half a year. Earthquake effects on CCC demand last up to eleven months after the event, with import demand reductions in the first six months of 4 to 20 percent, and slightly smaller (marginally) significant drops of about 11 to 16 percent in the second half.

Interestingly, storms show a statistically significant effect only on CCC export supply, while they show no statistically significant effect on CCC's import demand, see Figure 5. Supply drops consistently over the first twelve months after a major storm strikes a CCC. In the onset month,

Figure 3: Effects of Major Storms in Non-Credit-Constrained Countries, in Percent



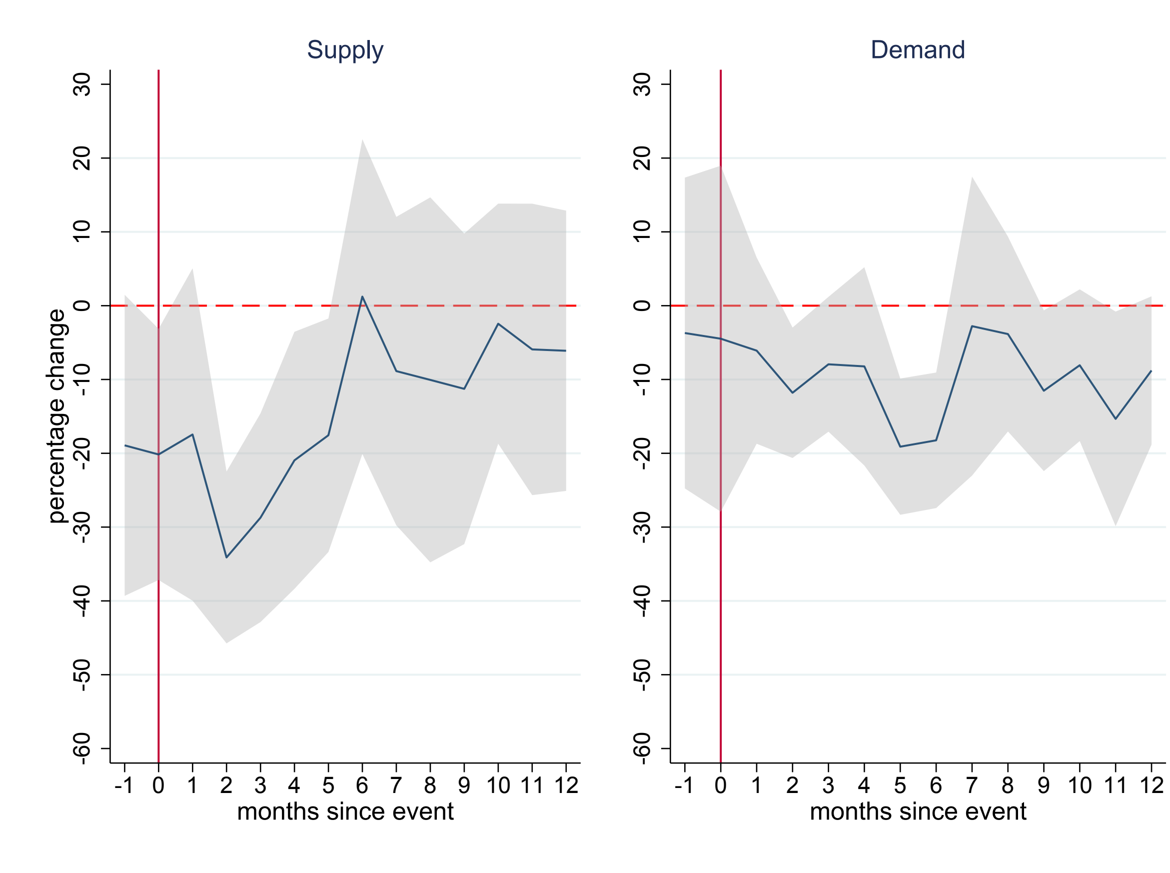
Notes: Figures show estimated percentage change effects of storms on monthly supply and demand. Percentage changes are calculated as $(\exp(\beta_k) - 1) \times 100$. 95% confidence intervals are calculated using the delta method. Estimates and confidence bands are taken from Table A4 columns (4) and (8) in the Appendix. One monthly lead and twelve monthly lags depicted on horizontal axis.

a major storm reduces CCC supply by 48 percent followed by a reduction of 48 to 29 percent in subsequent months. Effects from storms are comparably larger than those of earthquakes and spread more uniformly across subsequent months.

Overall, our results show that natural disasters have heterogeneous effects, both across country groups and disaster types. They more strongly affect countries which are credit-constrained due to high debt levels, their low development status, and lack of economic diversification. Overall, we cannot identify statistically significant supply or demand reducing effects for CCCs that last longer than twelve months after an earthquake event, while on the contrary, supply effects for storms may last longer. This points to the importance of using inter-annual data, as annual effects may mask the short-run adjustment dynamics.

Robustness. To check the robustness of the estimated demand and supply effects, we use linear and quadratic country-specific time trends on $\delta_i f(t)$. Table A5 in the Appendix presents the

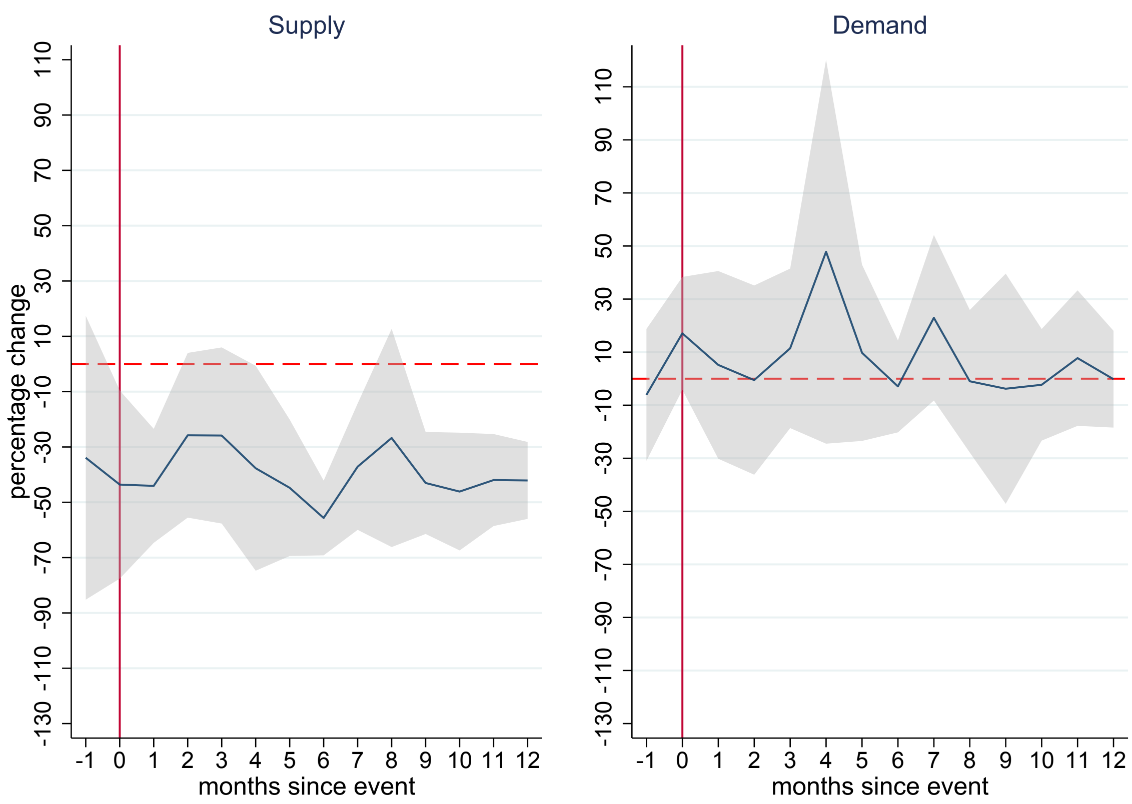
Figure 4: Effects of Major Earthquakes in Credit-Constrained Countries, in Percent



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. Estimates and confidence bands are taken from Table A4 columns (1) and (5) in the Appendix. One monthly lead and twelve monthly lags depicted on horizontal axis.

results. In our baseline regression, we use a cubic country-specific time trend to control for the growth path over time. As an alternative, we deploy a linear trend in Panel A of Table A5. In Panel B, we use a quadratic time trend. 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.

Figure 5: Effects of Major Storms in Credit-Constrained Countries, in Percent



Notes: Figures show estimated percentage change effects of storms 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. Estimates and confidence bands are taken from Table A4 columns (3) and (7) in the Appendix. One monthly lead and twelve monthly lags depicted on horizontal axis.

6 Counterfactual Welfare and Spillover Effects of Individual Disasters

6.1 Using the Model and Parameter Estimates for Counterfactual Simulations

The reduced form estimates of the supply and demand effects of disasters remain silent on their their general equilibrium effects, i.e., how they impact the economy as a whole. They also remain silent on how they spill over to third countries which are not directly affected by the disaster. These will depend on the trade network of a country and its trade relations with all its trading partners. Finally, the welfare implications of these effects remain to be established. In the following, we demonstrate how we can use our model and our parameter estimates to quantify these effects.

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.,

$$Y_{i,t} = \sum_{j=1}^{N} X_{ij,t} = w_{i,t}L_{i,t} + (1-\beta)Y_{i,t}, \tag{11}$$

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. Hence we can write

$$\begin{aligned}
Y_{it} &= \sum_{j=1}^{N} X_{ij,t} = \left(\frac{a_i c_{i,t}}{P_{j,t}}\right)^{1-\sigma} E_{j,t} && (12)\\
\frac{w_{i,t}L_{i,t}}{\beta} &= \sum_{j=1}^{N} X_{ij,t} = (a_i c_{i,t})^{1-\sigma} \sum_{j=1}^{N} \left(\frac{t_{ij,t}}{P_j}\right)^{1-\sigma} (1+d_{j,t})[w_{j,t}L_{j,t} + (1-\beta)Y_{j,t}] && (13)\\
w_{i,t}L_{i,t} &= \sum_{j=1}^{N} X_{ij,t} = (a_i c_{i,t})^{1-\sigma} \sum_{j=1}^{N} \left(\frac{t_{ij,t}}{P_j}\right)^{1-\sigma} (1+d_{j,t})w_{j,t}L_{j,t}, && (14)
\end{aligned}$$

where the last line again used $Y_{i,t} = w_{i,t}L_{i,t}/\beta$. Given the exogenous parameters, Equation (14) jointly with Equations (5) and (6) 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 trade and 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. Our estimated supply and demand effects of disaster events allow exactly this.

In light of Equations (6) and (8), we interpret the estimated supply effects of a disaster from Equation (10) as

$$\alpha_k = \Delta\mu_{i,k} = -(1-\sigma)\Delta \ln A_{i,k}, \tag{15}$$

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

$$\Delta \ln A_{i,k} = \frac{\alpha_k}{-(1-\sigma)} = \frac{\alpha_k}{5.03}, \tag{16}$$

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 (8), we interpret the estimated demand effects of a disaster from Equation (10) as

$$\beta_k = \Delta\zeta_{j,k} = \Delta \ln E_{i,k} = \Delta \ln(1 + d_{j,k}) \approx \Delta d_{j,k}, \tag{17}$$

i.e., our estimated disaster effect is observationally equivalent to an exogenous monthly expenditure shock or shock to the trade balance.

To actually solve the system of equations given by Equation (14) 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.[15] We obtain estimated trade costs, t_{ijt}, from our estimates from Equation (9). 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. What remains are values for the (scaled) productivities, $A_{i,t}/a_i$. Equation (8) implies a simple way to uncover $A_{i,t}/a_i$ from the exporter fixed effects estimated by Equation (9):

$$\mu_{i,t} = (1-\sigma)\ln\left(a_i c_{i,t}\right) = (1-\sigma)\ln\left(\frac{a_i w_{i,t}^{\beta} P_{i,t}^{1-\beta}}{A_{i,t}}\right). \tag{18}$$

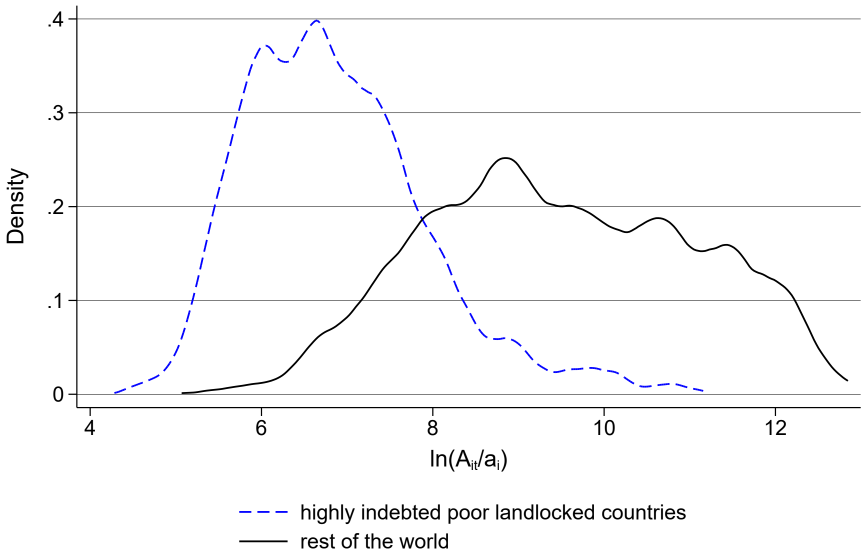
We can calculate $A_{i,t}/a_i$ from the exporter fixed effect using GDP per capita in year t as a proxy for a country's level of unit production costs, $w_{i,t}^{\beta} P_{i,t}^{1-\beta}$, and again assuming $(1-\sigma) = -5.03$, we can solve Equation (18) for $A_{i,t}/a_i$:

$$\ln\left(\frac{A_{i,t}}{a_i}\right) = \ln w_{i,t}^{\beta} P_{i,t}^{1-\beta} - \frac{\mu_{i,t}}{1-\sigma} = \ln\left(\text{GDP p.c.}\right)_{i,t} + \frac{\mu_{i,t}}{5.03}. \tag{19}$$

Without loss of generality, in our simulations, we normalize $A_{USA,t}/a_{USA} = 1$. We use Equation

[15] 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.

Figure 6: Distribution of Estimated Productivity Parameters



Notes: Figure shows the distribution of estimated monthly preference-scaled productivity parameters, $A_{i,t}/a_i$, in our sample for the group of heavily indebted poor landlocked countries as well as the rest of the world.

(19) to calculate monthly productivity at the time of the disaster event. Note that Eaton and Kortum (2002) use a similar method to estimate the productivity of countries and Costinot et al. (2012) also deploy exporter fixed effects to measure the export capacity of a country.

6.2 Validation of Estimated Productivity Parameters

For a credible simulation of the welfare and spillover effects of disasters, a key ingredient are plausible estimates of the (scaled) productivity parameters $A_{i,t}/a_i$ for all countries in our sample. Figure 6 shows the distribution of the estimated productivity parameters split into two groups of countries, heavily indebted poor landlocked countries (67 in total) and the rest of the world. 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 rest of world, reflecting the fact that this group not only contains high-income countries but also low-income countries with low debt levels.

To validate our estimated productivity parameters using external data, we would like to compare our estimates to other monthly measures of productivity or total factor productivity (TFP) data for a large set of countries. Monthly productivity measures for a large set of country do not exist. Fernald (2014) presents TFP for the U.S., albeit at a quarterly frequency.[16] We therefore calculate the quarterly average of our monthly productivity measures. TFP measures like those

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

calculated by Fernald (2014) are used to identify business cycles by applying filtering techniques. We therefore apply the Christiano and Fitzgerald (2003) band pass filter used by Fernald (2014) to filter outer cyclical components of less than six and more than 32 quarters (including a drift parameter), following the standard in the 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 7. The correlation between the two time series is 0.36. Hence our method does pick up some part of the variance of other, typically used TFP methods, at least for the U.S. We should not expect a too high correlation, however. 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. Also note that we do not use the time series variation in our productivity measure for identifying the welfare and spillover effects of disasters. Instead, we use the productivity parameters estimated according to Equation (19) at the time of the event across all countries to pin down cross-country productivity differences. The time variation we do use is the variation in our monthly trade data to estimate the trade effects of disasters. Hence, mismeasurement of the time series dynamics of our monthly productivity measures would only be a problem if this mismeasurement were systematically correlated with monthly trade dynamics and disasters. Given that we allow for country-specific trade dynamics via our country-specific month effects, we consider this a minor problem.

Overall, while not perfect, our method picks up productivity differences across countries and across time reasonably well. Importantly, it can be easily applied to a large sample of countries using only trade data. Typically, TFP estimates need detailed data on both domestic output and production factor use in order to identify TFP as a residual in output growth decomposition.

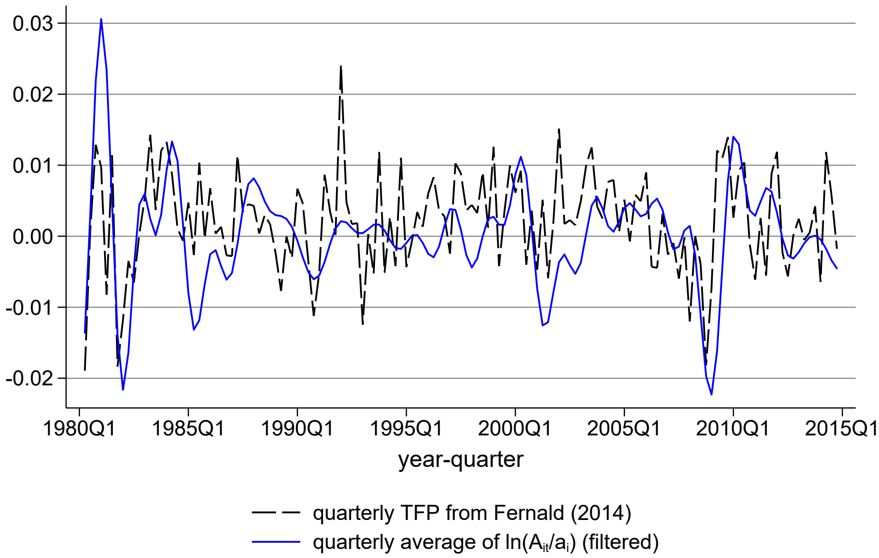
6.3 Welfare Effects of Individual Disasters

We quantify the dynamics of the per-period welfare effects of two prominent disasters: The 1992 Earthquake which hit Nicaragua in September 1992, and the Tohoku Earthquake in Japan 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.[17]

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

Figure 7: Comparison with Quarterly TFP Data for the United States



Notes: Figure shows the quarterly TFP measure calculated by Fernald (2014) 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.

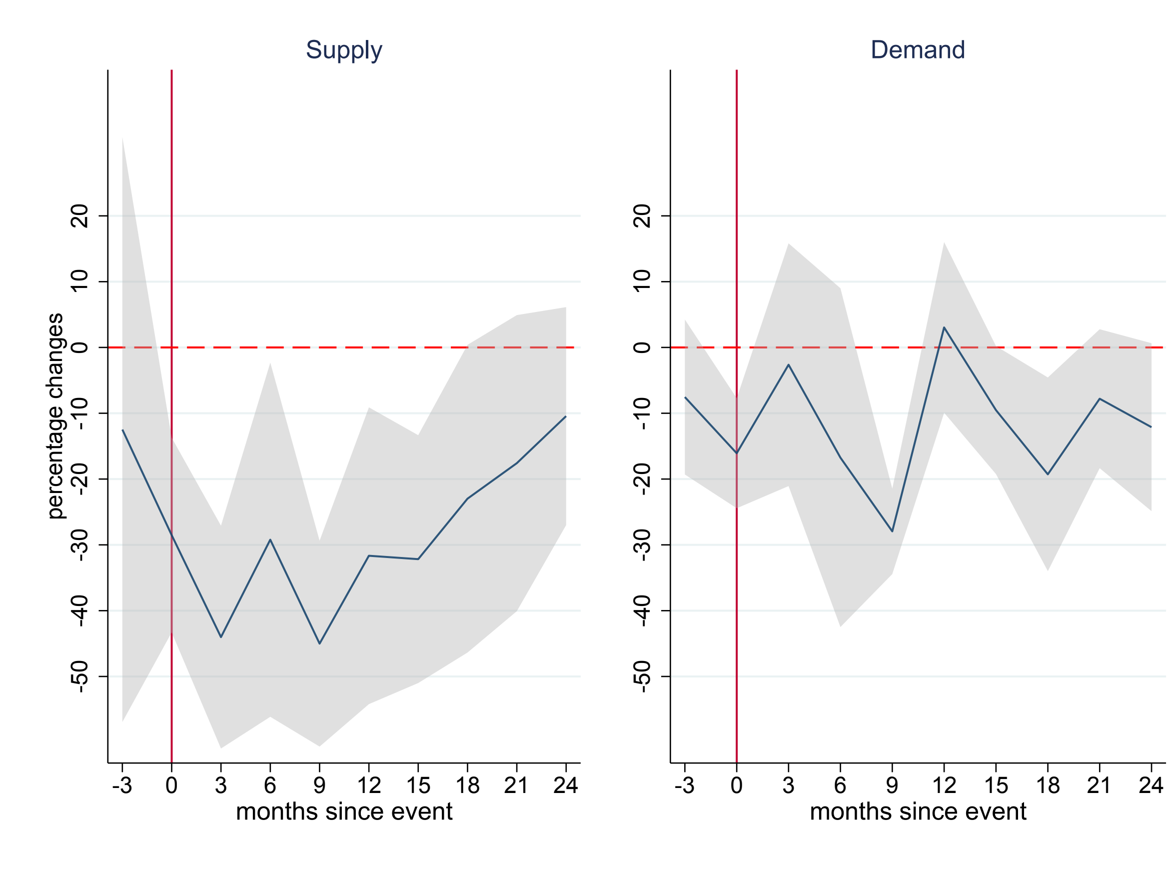
The Tohoku earthquake hit Japan in March 2011 with a magnitude of 9.1 M_w. It was the most powerful earthquake ever recorded in Japan. The quake triggered a tsunami that reached heights of up to 40.5 meters and traveled up to 10,000 meters inland. The estimated total damage was 360 billion U.S. dollar, but the Bank of Japan offered 183 billion U.S. dollar to normalize market conditions already three days after the disaster hit and the World Banks estimated economic costs was 235 billion U.S. dollar, making it the costliest natural disaster in history.

To get the supply and demand effects of these specific disasters, we re-estimate Equations (10) and (10) 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 also control for all other earthquake events in Nicaragua or Japan of magnitudes 6 (strong events that cause a lot of damage in very populated areas as classified by UPSeis) and higher. We report coefficient 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).[18] in Figure 8 for Nicaragua and in Figure 9 for Japan.

For both events, supply falls considerably in the month of the earthquake and tsunami ($t = 0$)

[18]Table A6 provides the coefficient estimates underlying Figures 8 and 9. 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. 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.

Figure 8: 1992 Nicaragua Earthquake, Nicaragua, 09/1992

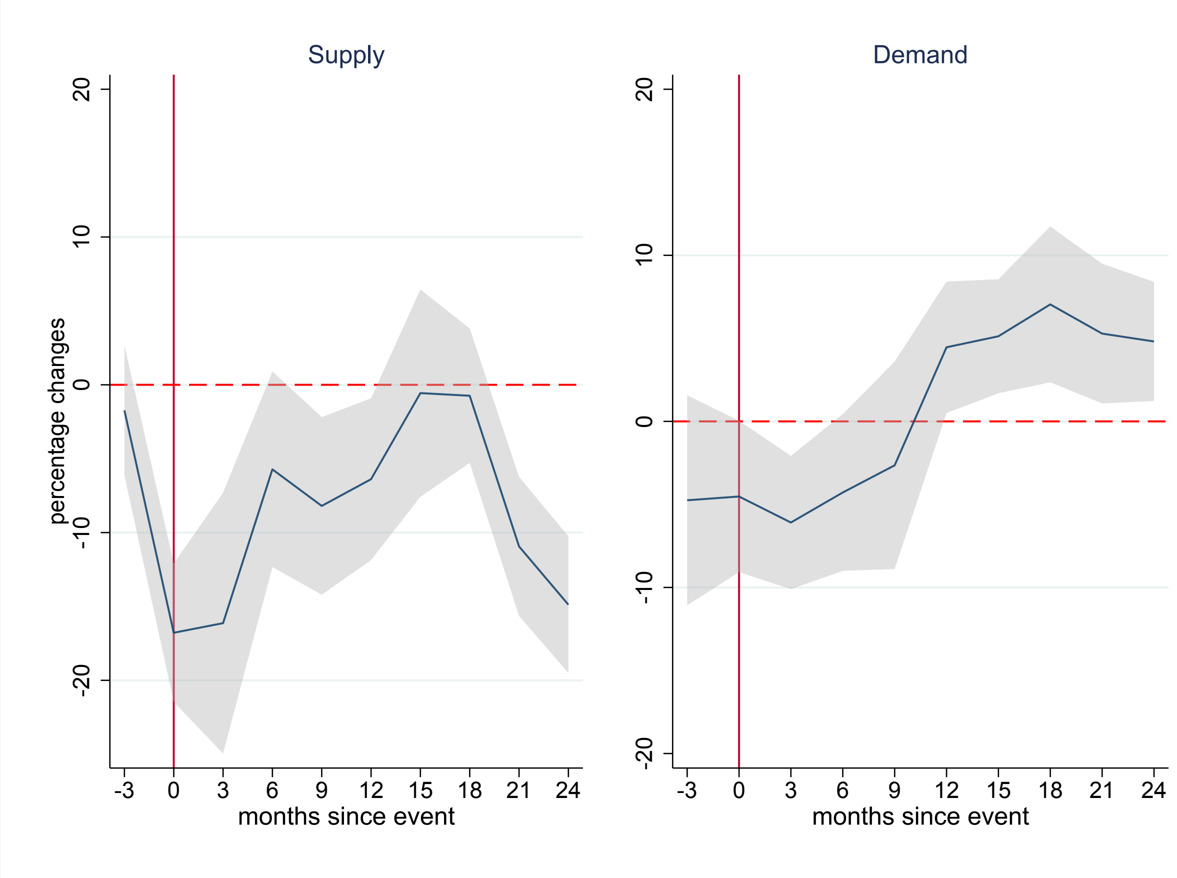


Notes: Figures show estimated percentage change effects of the Nicaragua earthquakes on supply and demand. Percentage changes are calculated as $(\exp(\beta_k) - 1) \times 100$. 95% confidence intervals are calculated using the delta method. Estimates and confidence bands are taken from Table A6 columns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

as well as the subsequent three months. Nicaragua's supplies fall by 30 percent in the month of the earthquake and remain 42 to 10 percent lower, showing quite a persistent negative effect on supply up to 23 months after the event (see column (1) of Table A6). Contrary to that, the Tohoku earthquake in Japan (column (2)) reduced exports between 16 and 8 percent in the year after the event, but returned to normal after that, with a second drop after 18 months, see also Figure 9. In sum, we find a large heterogeneity across the two countries and events, highlighting the need for an event-based analysis.

Turning to the demand-specific results, the 1992 Nicaragua earthquake (column (3)) has reduced demand-specific imports by 15 percent in the immediate month of the disaster and by up to 29 percent nine months later. Three and six months after the event, estimated effects are negative but small and not significant. But after 15 months, demand is still 10 percent below normal and stays 9 to 19 percent below for 18 to 24 months after the earthquake and tsunami hit in September 1992, see Figure 8. Contrary to that for the Tohoku earthquake in Japan, we find a

Figure 9: 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. Estimates and confidence bands are taken from Table A6 columns (1) and (3) in the Appendix. Control events include earthquakes in Japan above a magnitude of six Richter. Three- monthly (quarterly) lead and 24 (quarterly) monthly lags depicted on horizontal axis.

significant reduction of demand in the month of the earthquake as well as in up to eight months thereafter (column (4)). Thereafter, import demand increases by 4 to 7 percent one to two years after the event, probably highlighting a surge of demand to rebuild destroyed infrastructure and capital goods. This contrasts with the experience of Nicaragua, which saw its imports fall up to two years after the event. This probably reflects Nicaragua's lack of access to financial markets to finance rebuilding destroyed capital[19], while despite the massive damage in Japan, its National Bank intervened immediately, many more firms and private households are insured and Japan is able to attract finance from abroad despite its geological location in a disaster prone region.

We report results in Table 3. It shows the monthly change in welfare (i.e., real income) in the month of the disaster as well as the following three months. We assume that the labor force

[19]External debt in percent of Gross National Income in Nicaragua amounted to 1233.1 percent in 1989 and was reduced but still showed the massive amount of 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.

in all countries remains constant, so effects can be interpreted as changes in per capita welfare. For each disaster event, we use the estimated supply and demand effects from Table A6, i.e., we combine the effects of a change in imports and exports simultaneously. We then calculate the implied welfare changes compared to a counterfactual scenario where the disaster would not have happened. Note that we report quarterly (three-monthly) effects. In Table A8 in the Appendix, we report the same results but annualized (divided by 12) to see how the disaster affects annual real income.

Table 3: Model-implied Monthly Welfare Effects (in %)

Disaster Event	Earthquake	Tohoku Earthquake
Country	Nicaragua	Japan
Month/Year (t)	09/1992	3/2011
Direct Effect on Affected Country		
t	-19.3	-23.3
$t+3$	-24.5	-25.2
$t+6$	-19.9	-13.1
$t+9$	-32.9	-12.4
$t+12$	-15.1	1.9
$t+24$	-9.0	-6.5
Indirect Effect on Rest of the World (Median)		
t	-0.0	-0.8
$t+1$	-0.0	-0.9
$t+2$	-0.0	-0.4
$t+3$	-0.0	-0.4
$t+12$	-0.0	0.0
$t+24$	-0.0	-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.

For the 1992 earthquake, Nicaragua experienced a 19 percent reduction in per period welfare. The estimated large and persistent negative supply and demand effects mechanically translate into large and persistent negative welfare effects in the 24 months after the event. The Tohoku earthquake had even larger negative quarterly welfare effects in the month (23 percent) and the preceding quarter (25 percent) of the earthquake and tsunami, which is not surprising related to its magnitude and size. But the effects become less negative and even turn positive after 12 months, with a slight negative effect returning within the 24 months after the event.

Why are welfare effects so large? First, we assume that the labor share in production costs, β, is 0.21, i.e., 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. We have followed Eaton and Kortum (2002) and set $\beta = 0.21$, the value added share of labor in the manufacturing sector in their sample of OECD countries. 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.[20]

Our general equilibrium model also allows us to calculate the welfare effects of the natural disaster shock in the rest of the world. We report the median effect in all other countries in the sample. While the earthquake in Nicaragua had basically no effect on third countries, we find large spillover effects on third countries for the Tohoku earthquake. Why are spillovers so small? Anderson and van Wincoop (2003) show that in 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 GDP share. In 1992, Nicaragua had a world GDP share of 0.007 percent 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.[21] Japan's world GDP share in 2011 was close to 9 percent. Consequently, spillover effects on other countries are larger, but still quite small, between 0.2 and -0.8 percent, depending on the month. This is consistent with results by Behar and Nelson (2014) who also find only small general equilibrium effects of bilateral trade cost changes except for large countries. As we simulate the natural disasters as only hitting one country, the same intuition applies to our setting.[22] 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 GDP 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.

6.4 Disentangling the Productivity, Expenditure, and Trade Cost Channels

Our model allows us to disentangle the welfare effect of the natural disasters into its supply or productivity and expenditure or demand shock components to quantify their relative importance. This also allows us to shed light on the role trade costs in determining the size of the spillover

[20] 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).

[21] 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).

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

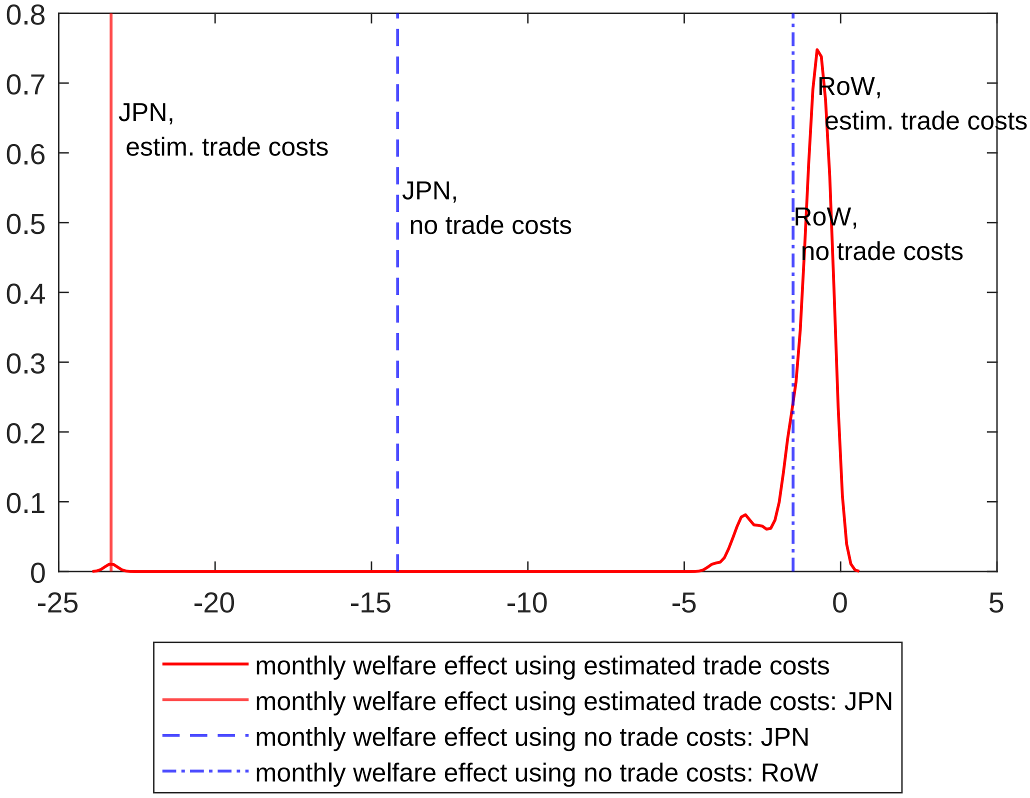
Table 4: Model-implied Monthly Welfare Effects: Impact of Trade Costs for the Tohoku Earthquake, Japan

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 $\Delta A_{i,t}$ & $\Delta d_{i,t}$
Direct Effect on Affected Country						
t	-16.1	-8.6	-23.3	-9.6	-5.0	-14.2
$t+3$	-15.5	-11.6	-25.2	-9.2	-6.8	-15.4
$t+6$	-5.4	-8.1	-13.1	-3.2	-4.8	-7.8
$t+9$	-7.8	-5.0	-12.4	-4.6	-2.9	-7.4
$t+12$	-6.1	8.5	1.9	-3.5	4.8	1.1
$t+24$	-14.3	9.1	-6.5	-8.5	5.2	-3.8
Indirect Effect on Rest of the World (Median)						
t	-0.6	-0.3	-0.8	-1.0	-0.5	-1.5
$t+3$	-0.6	-0.4	-0.9	-1.0	-0.7	-1.7
$t+6$	-0.2	-0.3	-0.4	-0.3	-0.5	-0.8
$t+9$	-0.3	-0.2	-0.4	-0.5	-0.3	-0.8
$t+12$	-0.2	0.3	0.0	-0.4	0.5	0.1
$t+24$	-0.5	0.3	-0.2	-0.9	0.5	-0.4

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.

effects on other countries. For this, we focus on the Tohoku earthquake. We present results in Table 4. We present the implied annualized effects in Table A9. The first three columns of Table 4 show the quarterly welfare effects using the estimated trade costs. The third column repeats the welfare effects from Table 3, i.e., the effect of the combined supply and demand shock ($\Delta A_{i,t}$ & $\Delta d_{i,t}$), whereas the first column presents the results when we shock the economy only by the estimated supply effect (only $\Delta A_{i,t}$) or, in the second column, only by the estimated demand effect (only $\Delta d_{i,t}$). Comparing the three columns makes clear that both the supply and the demand shock can be substantial. Importantly, both effects can have opposite directions, showing the complex effects of natural disasters on both export supply and import demand. The last three columns of Table 4 repeat the previous exercise but now in a counterfactual world without any trade costs. 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. 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

Figure 10: Distribution of Model-Based Monthly Welfare Effects of Tohoku Earthquake



Notes: Figure shows the distribution of monthly welfare effects of the Tohoku Earthquake in Japan in the immediate month of the onset of the disaster, once for the model using the trade costs estimated from the trade data, and once for a model without any trade costs. RoW refers to all other countries except Japan.

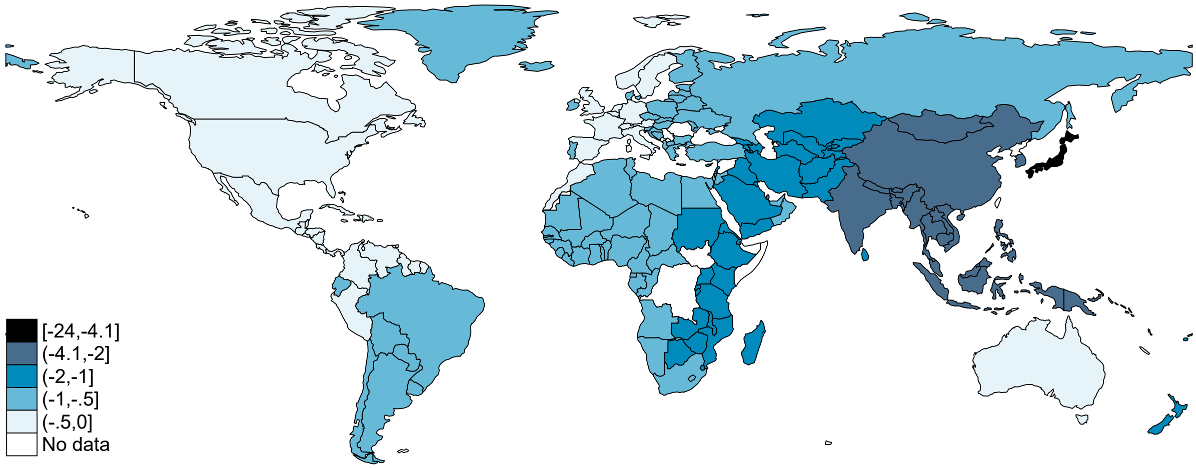
this "insurance" effect for the affected country comes purely from the lower trade costs and does not depend on the existence of an actual insurance against negative shocks such as a disaster. From this perspective, trade liberalization can mitigate the negative effects of natural disasters. The effects can be substantial: The negative welfare effect in the month of the disaster is about 40 percent smaller (-23.3 vs. -14.2 percent).

We show the distribution of the welfare effects ($\Delta A_{i,t}$ & $\Delta d_{i,t}$) in the month of the earthquake in Figure 10, contrasting the effects with and without trade costs. Note that without trade costs, all countries in the Rest of the World (RoW) face the same spillover effect.[23] We see that some countries experience a higher level of welfare in the world with trade costs compared to the no trade cost scenario, whereas for other countries the reverse is true.

Figure 11 shows spillover effects from the Tohoku earthquake in Japan to all other countries

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

Figure 11: 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.

in the world in the month when the earthquake and tsunami hit in a world with trade costs. Geographically closer economies, or economies with a regional trade agreement with Japan, are hit harder by the spillover effects relative to other economies.

This insurance effect of lower trade costs, however, is only present for natural disasters when they hit large economies. This can be seen when repeating the exercise in Table 4 for the 1992 earthquake in Nicaragua. We present results in Table 5 and Figure 12, and annualized effects in Table A10 in the Appendix. For Nicaragua, the insurance effect is absent, and absolute magnitudes in the scenario without trade costs are even slightly larger. Why is this the case? The answer lies in the fact that the insurance effect is related 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 still sell goods. Consequently, when a small country like Nicaragua is hit by a natural disaster, its negative productivity shock impacts welfare more in a world without trade costs.

7 Conclusion

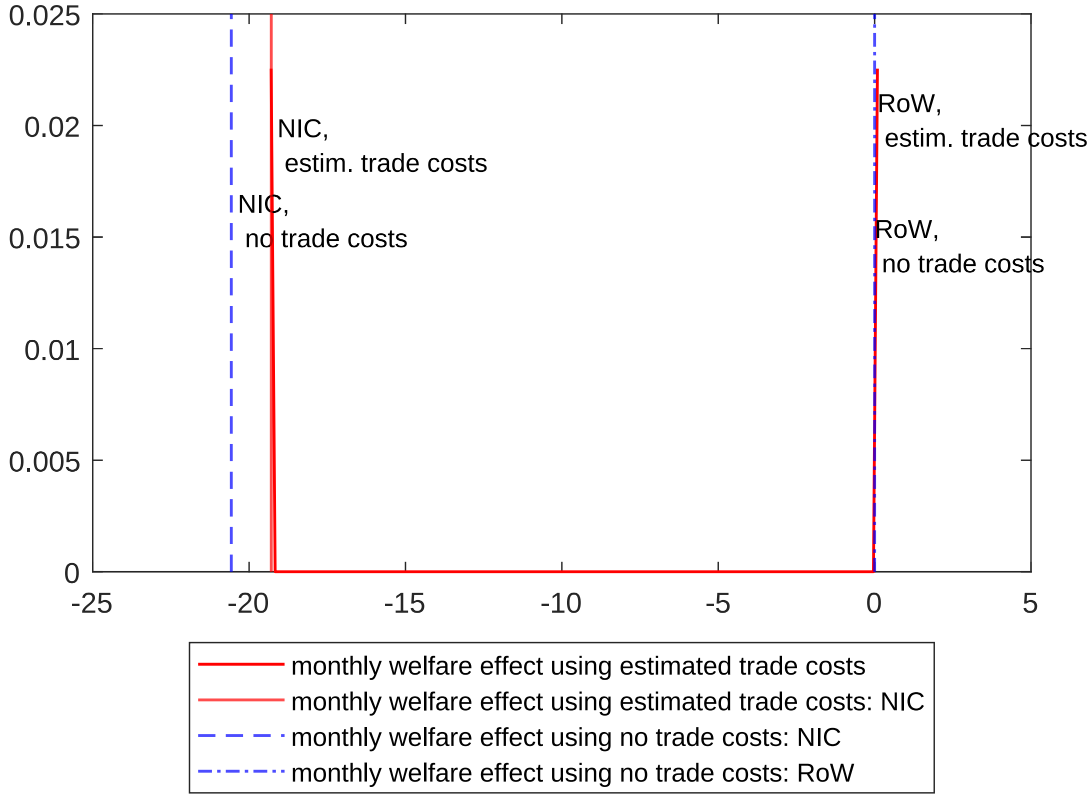
The economic consequences of natural disasters are still poorly understood. We present a simple quantitative trade model which allows us to identify the supply, demand and welfare effects of disasters from monthly trade data. Using a large panel of monthly merchandise import and export data and the ifo gridded GAME database of physical intensities of natural disasters, we quantify the effects of two types of short-onset disasters: earthquakes and storms. We document

Table 5: Model-implied Monthly Welfare Effects: Impact of Trade Costs for the 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 $\Delta A_{i,t}$ & $\Delta d_{i,t}$
Direct Effect on Affected Country						
t	-14.2	-6.0	-19.3	-15.5	-6.0	-20.6
$t+3$	-23.8	-0.9	-24.5	-25.9	-0.9	-26.6
$t+6$	-14.6	-6.2	-19.9	-16.0	-6.2	-21.2
$t+9$	-24.4	-11.1	-32.9	-26.6	-11.1	-34.8
$t+12$	-16.0	1.0	-15.1	-17.5	1.0	-16.7
$t+24$	-4.8	-4.4	-9.0	-5.3	-4.4	-9.4
Indirect 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 monthly welfare effects in percent, where welfare is measured as monthly real income. t is the month of the disaster event.

Figure 12: Distribution of Model-Based Monthly Welfare Effects of the 1992 Earthquake in Nicaragua



Notes: Figure shows the distribution of monthly welfare effects of the 1992 Earthquake in Nicaragua in September 1992 in the immediate month of the onset of the disaster, once for the model using the trade costs estimated from the trade data, and once for a model without any trade costs. RoW refers to all other countries except Nicaragua.

a large heterogeneity of the economic effects of disasters. While developed economies are typically unaffected by disasters, least developed, landlocked and heavily indebted countries suffer most.

Our estimated model allows us to quantify the welfare effects of a disaster as well as its spillover effects on its trade partners. We apply it to the 1992 earthquake and tsunami in Nicaragua, a financially-constrained country, and the Tohoku earthquake and tsunami in Japan in 2011, a developed economy. Our results illustrate that a country's trade costs with its trade partners play a crucial role in determining the size of spillovers.

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 the way how to respond to such disasters: When negative welfare effects of disasters mostly operate via negative 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 productivity, i.e., supply effects point to alleviating the financing needs of the private sector to rebuild destroyed production capacity.

Our quantitative framework is simple enough to be applied particularly to countries where other, more detailed data are not available, and can be applied to other natural disaster types. More broadly, our study should be seen as a first step towards using trade data to identify aggregate short-run fluctuations in economic activity from trade data.

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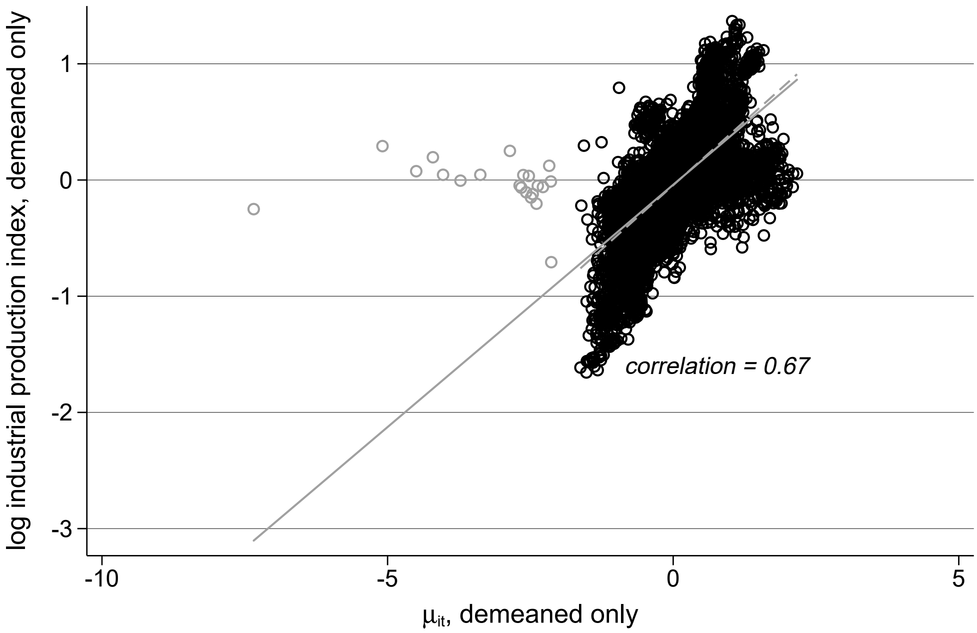
Appendix

Further Tables and Figures

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

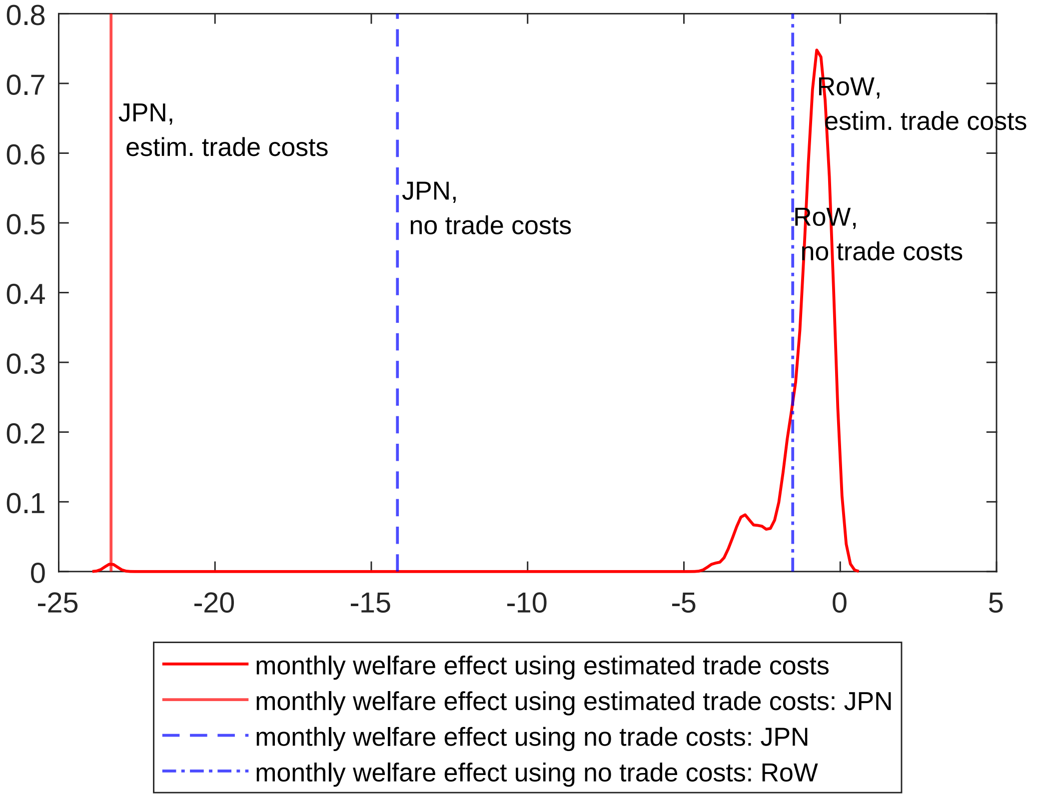
Variable	**Observations**	**Mean**	**St. Dev.**	**Min.**	**Max.**
ln Exports	68,396	20.774	2.805	7.365	27.707
ln Imports	68,396	21.247	2.332	11.791	27.668
ln Imports (fob)	68,396	21.239	2.341	10.255	27.626
$\ln \mu$	68,390	3.502	2.345	-4.830	9.691
$\ln \zeta$	68,396	3.980	1.898	-3.587	10.065
Earthquake, 95 Percentile	68,396	0.005	0.070	0	1
Storm, 95 Percentile	68,396	0.050	0.217	0	1
Earthquake, 75 Percentile	68,396	0.008	0.091	0	1
Storm, 75 Percentile	68,396	0.247	0.431	0	1
Earthquake, Intensity	68,396	1	10.079	0	199.590
Storm, Intensity	68,396	1	0.264	0.289	5.827

Figure A1: Correlation of Estimated Supply Parameters with Observed Industrial Production, Demeaned Only



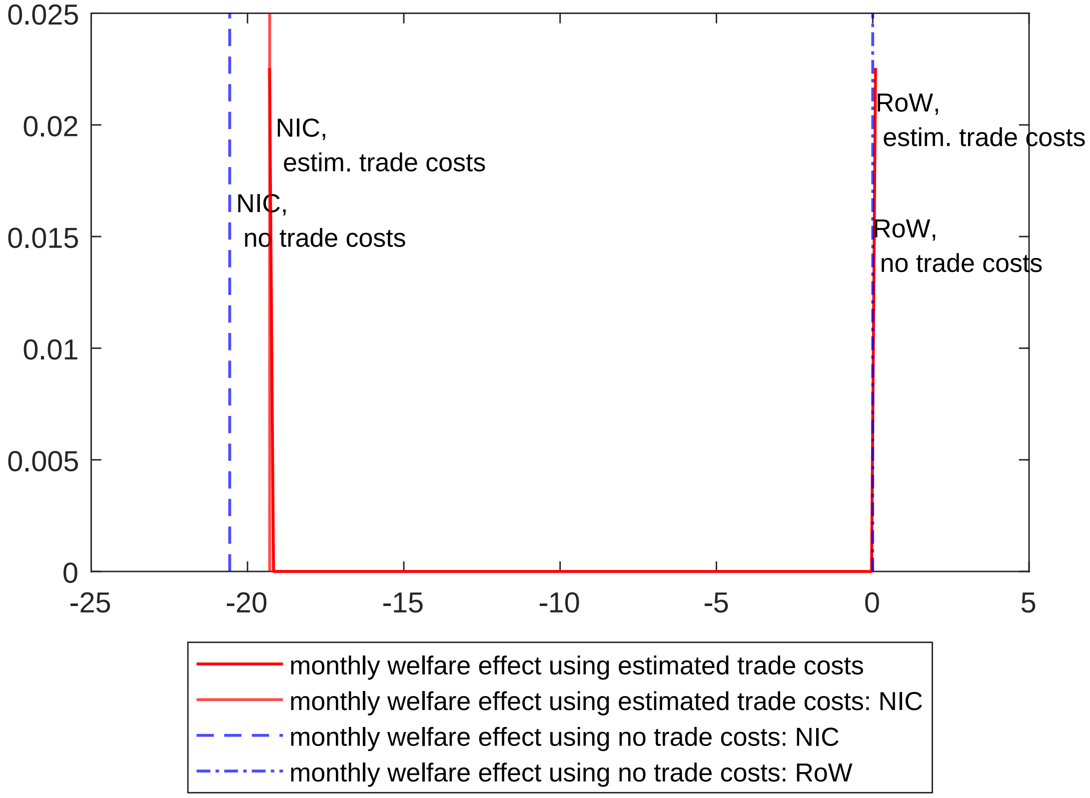
Notes: Figure shows a scatterplot and fitted regression line (in grey). We regress both our estimated monthly supply parameters, $\mu_{i,t}$, and the observed (log) monthly industrial production index from the IMF's International Financial Statistics on a set of country dummies to take into account the different base years across countries used for the production index. We then calculate the residuals from these two regressions and plot their scatterplot. The grey solid line depicts the predictions of a linear regression between the two series using all observations. The dashed grey line depicts the predictions of a linear regression which excludes 21 outliers (marked by grey circles) for which $\mu_{i,t}$<-2. The correlation between the two series excluding the outliers is 0.69. The outliers are 2011/4 for Côte d'Ivoire, 1997/1 for Luxembourg, 1992/1,4-11 for Kyrgyz Republic, and 1995/1-6,8-11 for Serbia. Data are from January 1980 to December 2014. Compared to Figure 1, the data in this figure are neither detrended nor deseasonalized, only demeaned.

Figure A2: Distribution of Model-Based Annualized Welfare Effects of Tohoku Earthquake



Notes: Figure shows the distribution of monthly welfare effects of the Tohoku Earthquake in Japan in the immediate month of the onset of the disaster, once for the model using the trade costs estimated from the trade data, and once for a model without any trade costs. RoW refers to all other countries except Japan.

Figure A3: Distribution of Model-Based Annualized Welfare Effects of the 1992 Earthquake in Nicaragua



Notes: Figure shows the distribution of monthly welfare effects of the 1992 earthquake in Nicaragua in September 1992 in the immediate month of the onset of the disaster, once for the model using the trade costs estimated from the trade data, and once for a model without any trade costs. RoW refers to all other countries except Nicaragua.

Table A2: Country Samples (1980 - 2014)

Country	**LDCs, HIPCs & LLDCs**	**RoW**	**Country**	**LDCs, HIPCs & LLDCs**	**RoW**
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	LDCs, HIPCs & LLDCs	RoW
Malaysia	0	1
Maldives	1	0
Mali	1	0
Malta	0	1
Mauritania	1	0
Mauritius	0	1
Mexico	0	1
Micronesia, Federated States of	0	1
Moldova	1	0
Mongolia	1	0
Morocco	0	1
Mozambique	1	0
Myanmar	1	0
Namibia	0	1
Nepal	1	0
Netherlands	0	1
New Zealand	0	1
Nicaragua	1	0
Niger	1	0
Nigeria	0	1
Norway	0	1
Oman	0	1
Pakistan	0	1
Panama	0	1
Papua New Guinea	0	1
Paraguay	1	0
Peru	0	1
Philippines	0	1
Poland	0	1
Portugal	0	1
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
Somalia	1	0
South Africa	0	1
Spain	0	1
Sri Lanka	0	1
Sudan	1	0
Suriname	0	1
Swaziland	1	0
Sweden	0	1
Switzerland	0	1
Syrian Arab Republic	0	1
Tajikistan	0	1
Tanzania	1	0
Thailand	0	1
Togo	1	0
Tonga	0	1
Trinidad and Tobago	0	1
Tunisia	0	1
Turkey	0	1
Turkmenistan	1	0
Uganda	1	0
Ukraine	0	1
United Arab Emirates	0	1
United Kingdom	0	1
United States	0	1
Uruguay	0	1
Uzbekistan	1	0
Vanuatu	1	0
Venezuela	0	1
Viet Nam	0	1
Yemen	1	0
Zambia	1	0
Zimbabwe	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)	−0.2098	−0.1682	−0.4139	−0.0171	−0.0378	0.1654	−0.0630	0.0266
	(0.13)	(0.19)	(0.40)	(0.08)	(0.11)	(0.17)	(0.14)	(0.05)
Event (t)	−0.2251**	−0.2067	−0.5726*	−0.0309	−0.0458	0.0968	0.1577*	0.0540
	(0.11)	(0.20)	(0.31)	(0.09)	(0.13)	(0.15)	(0.09)	(0.04)
Event (t+1)	−0.1918	0.0996	−0.5809***	−0.0418	−0.0628	−0.1742	0.0506	0.0839*
	(0.14)	(0.27)	(0.19)	(0.07)	(0.07)	(0.15)	(0.17)	(0.04)
Event (t+2)	−0.4172***	−0.2123	−0.2980	−0.0319	−0.1256**	−0.1189	−0.0054	0.0242
	(0.09)	(0.14)	(0.20)	(0.07)	(0.05)	(0.13)	(0.18)	(0.05)
Event (t+3)	−0.3386***	0.0699	−0.2991	−0.0345	−0.0827	−0.0211	0.1083	0.0941**
	(0.10)	(0.28)	(0.22)	(0.08)	(0.05)	(0.19)	(0.14)	(0.04)
Event (t+4)	−0.2351**	0.2006	−0.4731	−0.0465	−0.0858	−0.0529	0.3911	0.0147
	(0.11)	(0.31)	(0.30)	(0.07)	(0.07)	(0.11)	(0.25)	(0.05)
Event (t+5)	−0.1931**	0.3082	−0.5934***	−0.0796	−0.2120***	−0.0103	0.0931	0.1050**
	(0.10)	(0.26)	(0.23)	(0.09)	(0.06)	(0.16)	(0.15)	(0.04)
Event (t+6)	0.0123	0.1821	−0.8133***	−0.0814	−0.2014***	0.0556	−0.0295	0.0201
	(0.11)	(0.19)	(0.16)	(0.09)	(0.06)	(0.16)	(0.09)	(0.03)
Event (t+7)	−0.0928	0.0594	−0.4640**	0.0510	−0.0281	−0.0423	0.2067	0.0807*
	(0.12)	(0.29)	(0.19)	(0.10)	(0.11)	(0.18)	(0.13)	(0.04)
Event (t+8)	−0.1059	−0.0163	−0.3112	−0.0249	−0.0392	0.0206	−0.0098	0.0628
	(0.14)	(0.30)	(0.27)	(0.07)	(0.07)	(0.13)	(0.14)	(0.04)
Event (t+9)	−0.1196	0.1027	−0.5623***	0.1476	−0.1225*	−0.0449	−0.0385	0.0874**
	(0.12)	(0.38)	(0.17)	(0.10)	(0.06)	(0.16)	(0.23)	(0.04)
Event (t+10)	−0.0247	0.2109	−0.6185***	0.0416	−0.0841	0.0848	−0.0234	0.0152
	(0.09)	(0.24)	(0.20)	(0.08)	(0.06)	(0.16)	(0.11)	(0.04)
Event (t+11)	−0.0611	0.1169	−0.5440***	−0.0281	−0.1665*	0.0557	0.0747	0.0460
	(0.11)	(0.18)	(0.15)	(0.07)	(0.09)	(0.15)	(0.12)	(0.04)
Event (t+12)	−0.0630	−0.1437	−0.5464***	−0.0997	−0.0919	−0.0515	−0.0020	0.0549
	(0.10)	(0.26)	(0.12)	(0.09)	(0.06)	(0.12)	(0.09)	(0.05)
R^2	0.958				0.973			

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. Observations: 66,014.

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)	−1876	−0.1314	−0.3775	0.0423	−0.0226	0.1367	−0.0691	0.0356
	(0.13)	(0.21)	(0.41)	(0.06)	(0.11)	(0.16)	(0.12)	(0.05)
Event (t)	−0.2023**	−0.1621	−0.5398*	0.0273	−0.0301	0.0696	0.1493	0.0629
	(0.10)	(0.23)	(0.32)	(0.07)	(0.12)	(0.11)	(0.10)	(0.04)
Event (t+1)	−0.1717	0.1493	−0.5505***	0.0131	−0.0484	−0.1990*	0.0422	0.0923**
	(0.14)	(0.28)	(0.20)	(0.06)	(0.07)	(0.10)	(0.17)	(0.05)
Event (t+2)	−0.3975***	−0.1607	−0.2673	0.0296	−0.1109**	−0.1432*	−0.0136	0.0375
	(0.10)	(0.17)	(0.22)	(0.06)	(0.05)	(0.08)	(0.19)	(0.05)
Event (t+3)	−0.3202***	0.1204	−0.2694	0.0261	−0.0695	−0.0455	0.1008	0.1059***
	(0.10)	(0.29)	(0.24)	(0.07)	(0.05)	(0.14)	(0.14)	(0.04)
Event (t+4)	−0.2172*	0.2534	−0.4408	0.0155	−0.0733	−0.0766	0.3868	0.0265
	(0.11)	(0.33)	(0.32)	(0.06)	(0.07)	(0.09)	(0.24)	(0.04)
Event (t+5)	−0.1692*	0.3637	−0.5602**	−0.0290	−0.1997***	−0.0332	0.0894	0.1122***
	(0.10)	(0.25)	(0.24)	(0.07)	(0.05)	(0.13)	(0.15)	(0.04)
Event (t+6)	0.0362	0.2380	−0.7802***	−0.0317	−0.1884***	0.0335	−0.0329	0.0267
	(0.10)	(0.19)	(0.16)	(0.07)	(0.05)	(0.13)	(0.09)	(0.03)
Event (t+7)	−0.0702	0.1172	−0.4304**	0.1005	−0.0153	−0.0634	0.2034*	0.0874**
	(0.12)	(0.32)	(0.20)	(0.09)	(0.10)	(0.15)	(0.12)	(0.04)
Event (t+8)	−0.0857	0.0428	−0.2775	0.0234	−0.0249	0.0009	−0.0127	0.0695*
	(0.14)	(0.32)	(0.28)	(0.06)	(0.06)	(0.08)	(0.12)	(0.04)
Event (t+9)	−0.0985	0.1638	−0.5299***	0.1938**	−0.1058*	−0.0647	−0.0419	0.0936**
	(0.12)	(0.41)	(0.17)	(0.09)	(0.06)	(0.14)	(0.22)	(0.04)
Event (t+10)	−0.0035	0.2758	−0.5829***	0.0846	−0.0666	0.0677	−0.0310	0.0217
	(0.08)	(0.19)	(0.21)	(0.07)	(0.06)	(0.14)	(0.11)	(0.04)
Event (t+11)	−0.0399	0.1828	−0.5022***	0.0167	−0.1474*	0.0366	0.0709	0.0532
	(0.11)	(0.15)	(0.16)	(0.06)	(0.09)	(0.12)	(0.11)	(0.04)
Event (t+12)	−0.0398	−0.0708	−0.5061***	−0.0591	−0.0726	−0.0699	−0.0064	0.0581
	(0.10)	(0.25)	(0.14)	(0.08)	(0.05)	(0.09)	(0.09)	(0.05)
R^2	0.963				0.975			
Panel B: Quadratic Country-Specific Time Trend								
Event (t-1)	−0.1935	−0.1730	−0.4108	0.0073	−0.0299	0.1535	−0.0740	0.0310
	(0.13)	(0.19)	(0.40)	(0.07)	(0.11)	(0.16)	(0.13)	(0.05)
Event (t)	−0.2086**	−0.2086	−0.5720*	−0.0069	−0.0377	0.0855	0.1454	0.0583
	(0.10)	(0.20)	(0.31)	(0.08)	(0.12)	(0.14)	(0.10)	(0.04)
Event (t+1)	−0.1765	0.1012	−0.5810***	−0.0192	−0.0551	−0.1842	0.0386	0.0879*
	(0.14)	(0.27)	(0.19)	(0.07)	(0.07)	(0.13)	(0.17)	(0.05)
Event (t+2)	−0.4021***	−0.2097	−0.2979	−0.0064	−0.1177**	−0.1288	−0.0173	0.0303
	(0.09)	(0.15)	(0.21)	(0.07)	(0.05)	(0.11)	(0.18)	(0.05)
Event (t+3)	−0.3249***	0.0723	−0.2993	−0.0092	−0.0758	−0.0312	0.0969	0.0995**
	(0.10)	(0.28)	(0.23)	(0.07)	(0.05)	(0.17)	(0.14)	(0.04)
Event (t+4)	−0.2218**	0.2037	−0.4709	−0.0205	−0.0793	−0.0628	0.3812	0.0202
	(0.11)	(0.32)	(0.31)	(0.07)	(0.07)	(0.10)	(0.25)	(0.05)
Event (t+5)	−0.1773*	0.3125	−0.5906**	−0.0573	−0.2065***	−0.0200	0.0835	0.1091**
	(0.10)	(0.26)	(0.23)	(0.08)	(0.06)	(0.15)	(0.15)	(0.04)
Event (t+6)	0.0281	0.1867	−0.8106***	−0.0594	−0.1957***	0.0461	−0.0389	0.0240
	(0.10)	(0.19)	(0.16)	(0.08)	(0.05)	(0.15)	(0.09)	(0.03)
Event (t+7)	−0.0776	0.0648	−0.4610**	0.0731	−0.0225	−0.0514	0.1974	0.0847**
	(0.12)	(0.30)	(0.19)	(0.09)	(0.10)	(0.16)	(0.13)	(0.04)
Event (t+8)	−0.0907	−0.0099	−0.3081	−0.0031	−0.0324	0.0121	−0.0189	0.0668
	(0.14)	(0.31)	(0.28)	(0.07)	(0.07)	(0.11)	(0.13)	(0.04)
Event (t+9)	−0.1033	0.1102	−0.5606***	0.1687*	−0.1145*	−0.0535	−0.0481	0.0912**
	(0.12)	(0.39)	(0.17)	(0.10)	(0.06)	(0.15)	(0.22)	(0.04)
Event (t+10)	−0.0083	0.2200	−0.6148***	0.0615	−0.0757	0.0772	−0.0339	0.0190
	(0.08)	(0.22)	(0.21)	(0.08)	(0.06)	(0.15)	(0.11)	(0.04)
Event (t+11)	−0.0444	0.1257	−0.5381***	−0.0070	−0.1574*	0.0470	0.0653	0.0501
	(0.11)	(0.17)	(0.15)	(0.07)	(0.09)	(0.14)	(0.12)	(0.04)
Event (t+12)	−0.0460	−0.1322	−0.5414***	−0.0802	−0.0830	−0.0598	−0.0117	0.0576
	(0.10)	(0.25)	(0.13)	(0.09)	(0.05)	(0.11)	(0.09)	(0.05)
R^2	0.961				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. Observations: 66,014.

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)	−0.1332	−0.0174	−0.0783	−0.0487
	(0.20)	(0.02)	(0.06)	(0.03)
Event (t)	−0.3356***	−0.1837***	−0.1752***	−0.0463*
	(0.07)	(0.03)	(0.05)	(0.02)
Event (t+3)	−0.5802***	−0.1759***	−0.0266	−0.0628***
	(0.08)	(0.05)	(0.10)	(0.02)
Event (t+6)	−0.3455***	−0.0589	−0.1832	−0.0437*
	(0.13)	(0.04)	(0.16)	(0.03)
Event (t+9)	−0.5981***	−0.0855**	−0.3278***	−0.0268
	(0.08)	(0.03)	(0.05)	(0.03)
Event (t+12)	−0.3806***	−0.0660**	0.0300	0.0437**
	(0.11)	(0.03)	(0.06)	(0.02)
Event (t+15)	−0.3881***	−0.0056	−0.1000*	0.0500***
	(0.09)	(0.04)	(0.05)	(0.02)
Event (t+18)	−0.2611**	−0.0074	−0.2142**	0.0681***
	(0.11)	(0.02)	(0.09)	(0.02)
Event (t+21)	−0.1934*	−0.1158***	−0.0811	0.0515**
	(0.11)	(0.03)	(0.06)	(0.02)
Event (t+24)	−0.1102	−0.1611***	−0.1291*	0.0470***
	(0.08)	(0.03)	(0.07)	(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 lead and 24 monthly lags included. Control events include earthquakes in Nicaragua and Japan above a magnitude of 6 Richter. Observations: 64,226. R^2 is 0.959 for supply and 0.974 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)	−0.2997**	0.0495	−0.0513	0.0100
	(0.12)	(0.04)	(0.07)	(0.02)
Event	−0.3972***	−0.1329***	−0.1707**	−0.0520**
	(0.14)	(0.04)	(0.08)	(0.02)
Event (t+1)	−0.5894***	−0.1402***	0.1481**	−0.0287
	(0.10)	(0.03)	(0.07)	(0.03)
Event (t+2)	−0.4962***	−0.1670***	−0.0132	−0.0268
	(0.08)	(0.03)	(0.06)	(0.02)
Event (t+3)	−0.4473***	−0.0241	−0.0391	−0.0403
	(0.07)	(0.03)	(0.06)	(0.03)
Event (t+4)	−0.4501***	−0.0009	0.0111	−0.0176
	(0.08)	(0.04)	(0.05)	(0.02)
Event (t+5)	−0.4005***	−0.0431	0.1157*	−0.0153
	(0.10)	(0.04)	(0.07)	(0.03)
Event (t+6)	−0.0838	0.0137	−0.4198***	0.0122
	(0.09)	(0.04)	(0.06)	(0.03)
Event (t+7)	−0.5546***	−0.0318	−0.4897***	0.0242
	(0.10)	(0.05)	(0.07)	(0.03)
Event (t+8)	−0.6273***	−0.0925**	−0.2140***	0.0290
	(0.10)	(0.04)	(0.05)	(0.03)
Event (t+9)	−0.5527***	−0.0129	−0.3115***	0.0344
	(0.07)	(0.04)	(0.07)	(0.03)
Event (t+10)	−0.2652***	−0.0337	−0.1252*	0.1000***
	(0.08)	(0.04)	(0.06)	(0.03)
Event (t+11)	−0.2548*	−0.0212	0.0821	0.0950***
	(0.13)	(0.05)	(0.12)	(0.03)
Event (t+12)	−0.3355**	−0.0710	0.1913	0.0770***
	(0.13)	(0.05)	(0.12)	(0.03)

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 6 Richter. Observations: 66,014. R^2 is 0.958 for supply and 0.973 for demand.

Table A8: Model-implied Annualized Welfare Effects (in %)

Disaster Event	Earthquake	Tohoku Earthquake
Country	Nicaragua	Japan
Month/Year (t)	09/1992	3/2011
Direct Effect on Affected Country		
t	−1.6	−1.9
$t+3$	−2.0	−2.1
$t+6$	−1.7	−1.1
$t+9$	−2.7	−1.0
$t+12$	−1.3	0.2
$t+24$	−0.7	−0.5
Indirect Effect on Rest of the World (Median)		
t	0.0	−0.1
$t+1$	0.0	−0.1
$t+2$	0.0	0.0
$t+3$	0.0	0.0
$t+12$	0.0	0.0
$t+24$	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.

Table A9: Model-implied Annualized Welfare Effects: Impact of Trade Costs for the 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 $\Delta A_{i,t}$ & $\Delta d_{i,t}$
Direct Effect on Affected Country						
t	-1.3	-0.7	-0.2	-0.8	-0.4	-1.2
$t+3$	-1.3	-1.0	-0.2	-0.8	-0.6	-1.3
$t+6$	-0.5	-0.7	-0.1	-0.3	-0.4	-0.6
$t+9$	-0.6	-0.4	-0.1	-0.4	-0.2	-0.6
$t+12$	-0.5	0.7	0.0	-0.3	0.4	0.1
$t+24$	-1.2	0.8	-0.0	-0.7	0.4	-0.3
Indirect Effect on Rest of the World (Median)						
t	-0.0	-0.0	-0.0	-0.1	-0.0	-0.1
$t+3$	-0.0	-0.0	-0.0	-0.1	-0.1	-0.1
$t+6$	-0.0	-0.0	-0.0	-0.0	-0.0	-0.1
$t+9$	-0.0	-0.0	-0.0	-0.0	-0.0	-0.1
$t+12$	-0.0	0.0	0.0	-0.0	0.0	0.0
$t+24$	-0.0	0.0	-0.0	-0.1	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 4.

Table A10: Model-implied Annualized Welfare Effects: Impact of Trade Costs for the 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 $\Delta A_{i,t}$ & $\Delta d_{i,t}$
Direct Effect on Affected Country						
t	-1.2	-0.5	-0.1	-1.3	-0.5	-1.7
$t+3$	-2.0	-0.1	-0.2	-2.2	-0.1	-2.2
$t+6$	-1.2	-0.5	-0.1	-1.3	-0.5	-1.8
$t+9$	-2.0	-0.9	-0.2	-2.2	-0.9	-2.9
$t+12$	-1.3	0.1	-0.1	-1.5	0.1	-1.4
$t+24$	-0.4	-0.4	-0.1	-0.4	-0.4	-0.8
Indirect 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 5.