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Abstract

In this paper we combine sectoral input-output linkages based on the production network of 172 countries and 12 sectors from 1990 to 2015 and information on extreme weather events to construct an index measuring the intensity of shocks in the supply chain for each sector and country. This index is then used in an econometric model to determine the impact of supply chain disruptions on a sector's export performance. Our results suggest that a one standard deviation increase in our supply chain shock measure reduces a sector's export value by around 11 percent. Finally, we project that, if no additional adaptation were to occur, climate change will additionally reduce a sector's export value by up to 16 percent with a considerable heterogeneity in strength of the effect between the countries and sectors. Knowledge on the role of input-output linkages in the propagation of extreme weather shocks is important to design more resilient supply chains in future.

Keywords: Supply chain shock propagation, climate change, natural disasters, export.

JEL: F14; F18; Q54.

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1 Introduction

Every year numerous natural disasters happen worldwide. In 2018 only, 315 natural disaster occurred, which resulted in 11,804 deaths, 68 Million people affected and 131,7 billion USD in direct economic damages (CRED 2019).[1] There is a fair amount of literature focusing on the sectoral and macroeconomic outcomes of natural disasters (e.g., Raddatz 2007, Noy 2009, Skidmore & Toya 2002, Dell, Jones & Olken 2012, Cavallo, Galiani, Noy & Pantano 2013, Hsiang & Jina 2014, Felbermayr, Gröschl, Sanders, Schippers & Steinwachs 2018).[2]

Besides direct macroeconomic impacts, countries can also be affected by large natural disasters happening abroad, which are propagated globally over economic network structures. Economies today are organized in fine interwoven networks of production units - each commonly receiving input flows from their suppliers to produce products, which are then often used as inputs in other production units (Carvalho 2014). Idiosyncratic shocks, which are triggered for example by natural disasters, and affect only a specific production unit, can be widely dispersed in the economy through inter-industry linkages. A prominent example of such an event is the 2011 flood in Thailand, which affected 14,500 companies for automobiles and computers situated in the inundated area around Bangkok. After the event, Nissan and Toyota had to suspend production worldwide, because of problems in obtaining parts from Thailand. Also, global prices of hard disks doubled, because almost half of the world's hard disk supply were produced in Thailand (Liverman 2016). Another event, which is thoroughly studied in the recent literature, is the 2011 Tōhoku Earthquake in Japan, which had large, significant impacts on the US manufacturing industry (Barrot & Sauvagnat 2016, Boehm, Flaaen & Pandalai-Nayar 2019, Carvalho, Nirei, Saito & Tahbaz-Salehi 2016). Recent studies, which analyze the role of production networks in the propagation of shocks across sectors (Acemoglu, Carvalho, Ozdaglar & Tahbaz-Salehi 2012, Puzzello & Raschky 2014) or within sectors across firms (Barrot & Sauvagnat 2016, Boehm et al. 2019, Carvalho et al. 2016) give some empirical evidence on this relationship. The extend of this effect depends on the in- and outdegree distribution in the production network, i.e. the degree of connectivity between the production units.

In this paper, we provide empirical evidence of the effect of natural disaster schocks in the supply chain on a country's export activity. In particular, following Puzzello & Raschky (2014) we analyze how natural disasters propagate through sectors, which are strongly interconnected via input-output linkages, from country to country. To analyze the role of the global production networks in the propagation of shocks, we first construct a measure, which captures the degree of input-output connectivity between sectors and countries. We obtain information on input-output linkages for a large set of countries from 1990-2015 from the EORA global supply chain database (Lenzen, Kanemoto, Moran & Geschke 2012, Lenzen, Moran, Kanemoto & Geschke 2013). Second, we use a subset of extreme weather indices defined by the Expert Team on Climate Change Detection and Indices (Karl, Nicholls & Ghazi 1999, Sillmann, Kharin, Zhang, Zwiers & Bronaugh 2013) based on daily temperature and precipitation data, to construct proxies for

[1] The year 2018 was below the 10-year average, which is 348 natural disasters, 67,752 deaths, 198,8 million affected and 166,7 billion in direct economic damages.

[2] For a recent literature review on the macroeconomic impacts of natural disasters, see Botzen, Deschenes & Sanders (2019).

historical and projected future natural disasters. Finally, combining our variable of supply-chain interlinkages and our proxy for natural disasters, gives us a measure of supply chain shocks to a sector and country, which is then used in a fixed-effect model to estimate its impact on a sector's export performance. In a further step, as the frequency and intensity of natural disasters will increase in future due to climate change (e.g. Sillmann, Kharin, Zwiers, Zhang & Bronaugh 2013), we give insights in the prospective sectoral exposure to natural disaster shocks transmitted over the supply chain.

Our results highlight that supply chain disruptions, caused by large natural disasters abroad, significantly reduces a sector's export value. A one standard deviation increase in our supply chain shock measure reduces a sector's export value by around 11 percent. Further, we show that this negative effect is mainly driven by the manufacturing sector, which is due to the increasing internationalization of input sourcing, which has taken place in the in the manufacturing sector over time. Finally, predicting future supply chain shocks we find a potentially strong impact of climate change on the extension of the negative effects of supply chain shocks on a sector's export value. Depending on the global circulation model and the representative emission pathway climate change reduces exports via supply chain shocks by about 8 percent to 26 percent. The impact of climate change is heterogeneous between countries and sectors and depends on the extend of a sectors global production network and the strength of increase in natural disasters in that region. Our results suggest, that it is countries in the tropics and subtropics, which will be particularly negative affected by these shocks in future.

This paper contributes to the literature on the role of production networks in the propagation of shocks across sectors. Our study is based on sector level information for a large number of countries over a long period of time. Although, we are less disaggregated than recent studies based on within sectors across firms variation (Barrot & Sauvagnat 2016, Boehm et al. 2019, Carvalho et al. 2016) we are able to consider a multitude of different natural disaster shocks happening all over the globe. This allows us to account for country and sectoral specificities to deal with supply chain disruptions. Further, to the best of our knowledge this is the first study to examine a country and sectoral exposure to supply chain shocks taking climate change induced changes in the occurrence of natural disasters into account. Finally, our study relates to the literature studying the macroeconomic impacts of natural disasters (e.g., Cavallo et al. 2013, Felbermayr et al. 2018, Mohan, Ouattara & Strobl 2018). We add one potential mechanism how disasters can affect macroeconomic outcomes even in regions outside of the disaster affected area.

The insights of this study have important policy implications. Adaptation policies to current natural disasters as well as potential future disaster exposure need to take the vulnerability of sectors to supply chain disruptions into account. Pro-active measures to mitigate the impact of supply chain shocks can be based on information campaigns, regulation or firm-level insurance. At individual level, firms, for example, can increase their level of geographical diversification in their global production network or intensify the use of storage facilities. Re-active, post-disturbance measures, could be based on direct disaster relief aid to shorten the recovery period in the affected region and decrease the length of the supply chain disruption. However, the success of these post-disturbance measures relies on several country level-factors, like the quality of political and financial institutions.

This paper is structured as follows. Section 2 gives a conceptional discussion on the mechanism how natural disasters propagate through the supply chain. Further, a short review of the recent literature, which analyze the role of input-output linkages as a propagation mechanism of idiosyncratic productivity shocks, is given. Section 3 presents the empirical framework. In section 4 the data on supply chain vulnerability as well as the data on extreme weather events is introduced. Section 5 discusses the main results for the impact of supply chain vulnerability and present the climate change predictions. Finally, section 6 concludes.

2 Related literature and conceptual discussion

Natural disasters affect the productivity level of firms in a sector in different ways. They destroy tangible assets such as buildings and equipment as well as inventories, e.g., intermediate products and raw materials. Natural disasters can cause significant short term population changes due to reallocation and by this directly affect the available labor supply (e.g., Belasen & Polachek 2008, Kirchberger 2017). Finally, firms can be affected by demand effects due to a reallocation and loss of existing customers.[3] In the case a firm is directly affected by a natural disaster, its productivity shock may be propagated through the production network to it's customers as well as suppliers and, thereby, indirectly affect firms beyond the disaster region. To conceptualize this relationship, we build on the model of Carvalho et al. (2016), who examine the propagation of disaster shocks in the supply chain. In this model, a negative disaster shock to firm x can impact firms downstream in the production network, i.e., customers of firm x, and upstream firms, i.e., suppliers of firm x. Downstream firms are affected via two channels. First, a disaster shock to firm x decreases its productivity, which increases its price. Downstream firms buying its product have, therefore, to scale back production, which leads to a smaller output. Second, due to the price increase of firm x the downstream firm can substitute the affected input with labor, which, depending on the size and sign of the substitution elasticity leads to a further production decrease of the downstream firm. The effect on upstream firms - the suppliers to firm x - depends on whether labor and the affected inputs are gross substitutes or complements. The mechanism of the upstream propagation comes from the price change of firm x. As prices increase downstream firms buy less products, which leads the firm x to reduce its own input demand. Finally, the propagation effect decays in distance, i.e., the further away the downstream or upstream firm is from firm x in the supply chain, the smaller is the potential indirect disaster impact. This comes from the fact that the importance of a firm in an input-output relationship decreases the more intermediate steps are between these two firms.

Recently, a couple of studies came out, which analyzed the role of input-output linkages as a propagation mechanism of idiosyncratic productivity shocks.[4] Carvalho et al. (2016), using

[3] A change in demand can change the productivity level of firms in case firms face increasing economies of scale.

[4] This literature can in turn be placed in the larger strand of papers dealing with the microeconomic origins of macroeconomic fluctuations (e.g., Acemoglu et al. 2012, Acemoglu, Ozdaglar & Tahbaz-Salehi 2017). For a recent overview see Carvalho (2014).

an extensive dataset of supplier-customer relationships of Japanese companies, show that the 2011 earthquake in Japan had significant negative impacts on the output of firms downstream as well as upstream of the affected firms, with a larger negative effect for the downstream firms. Barrot & Sauvagnat (2016) based their research on US data and find that a shock to suppliers propagate within the country and leads to substantial output losses at their direct customers. In an earlier cross country study Puzzello & Raschky (2014) find on a sectoral level a significant negative effect of supply chain shocks on a sector's export value in that year. More recently, Boehm et al. (2019) base their analysis on between-country transmission of shocks using a database of American affiliates of Japanese multinationals. They show large output reductions in these companies compared to not-affiliated companies in the US in the months following the 2011 earthquake in Japan. Finally, in a recent working paper Kashiwagi, Todo & Matous (2018) analyze the impact of hurricane sandy on the output of 110.000 major firms worldwide. They find large propagation effects between firms within the country, but do not find significant impacts on output between firms across countries. They argue, that internationalized firms can more easily substitute for their suppliers and customers and are, therefore, able to mitigate the propagation of shocks.[5]

3 Empirical implementation

To answer our research questions, we specify a generic model that accounts for the impact of a natural disaster transmitted over the supply chain on a sector's exports as follows:

$$Y_{hit} = \beta_0 + \beta_1 SCS_{hit} + \beta_2 X_{hit} + \lambda_{ht} + \theta_{hi} + \zeta_{it} + \varepsilon_{hit}, \tag{1}$$

where Y_{hit} is the logged export value of sector, h, in country, i, and year, t. SCS_{hit}, is our parameter of interest and is the measure of the degree of a natural disaster shock transmitted over the supply chain to sector, h, country, i, in year, t. Based on our discussion on supply chain propagation of disaster shocks in section 2, we expect β_1 to be statistically significant. A nonzero coefficient estimate of SCS_{hit} implies that a sector's export performance is affected by disasters happening abroad and being transmitted over the supply chain. We expect β_1 to be negative as supply chain shocks reduce the average productivity of the firms in an affected sector. X_{hit}, is a vector of all sector characteristics in country i, which affect a sector's export intensity and which vary over time, e.g., the economic size of a sector or the degree of foreign competition.

λ_{ht}, is a sector-year dummy, which covers all factors that vary over sectors in a specific year and influence the export activity of a sector, e.g., business cycles. θ_{hi} is a country sector dummy, which controls for all sector specific factors in a country, which are invariant over time, e.g., the capital intensity of specific sectors in a country, which makes them relatively inelastic to adopt to short-term demand changes, or the degree of returns to scale. ζ_{it} is a country-year dummy,

[5] Another strand of literature uses simulation analysis based on CGE or agent based modeling to asses the impact of supply chain shocks on a firm's output. See, for example, Otto, Willner, Wenz, Frieler & Levermann (2017), Inoue & Todo (2019*a*) and Inoue & Todo (2019*b*).

which captures all country specific factors, which change over time, and have an effect on a sector's export performance, e.g., the occurrence of a domestic disaster or the financial crisis in the year 2008. Finally, the error term, ε_{hit}, is assumed to be i.i.d. and heteroscedasticity robust.

Based on our fixed effect structure, we should be able to disentangle the impact of an exogenous short-term supply chain shock on the exporters' productivity and the resulting export decision from other confounding factors. Our identification of an exogenous short-term supply chain shock comes by comparing the export performance of different sectors, which are differently exposed to supply chain shocks as they are differently embedded in the global supply chain network, in the same country as well as with the export performance of the same sector in different countries.

Finally, the coefficient estimate of SCS may be biased, if important variables are omitted, which are correlated with our supply chain shock measure and influence the export performance of a sector. In general, we are able to control for most of confounding variation through our very strict fixed effect structure. However, for instance, the size and experience of exporters could influence the way how supply chain shocks affect the export performance of a sector. Large and experienced exporters may have a more efficient management of their supply chains, which makes them more able to better react to supply chain shocks. In an extension of our model as specified in equation 2 we are controlling for exporter size and experience.

4 Data and summary statistics

Information on a country's worldwide export flows stems from the World integrated Trade Solutions (WITS) data base, which itself relies on the UN's commodity trade statistic database.[6] Data on a country's domestic and international input-output structures is taken from the EORA global supply chain database. The EORA global supply chain database is based on the supply-use tables from the full EORA multi-regional input-output tables, which have been converted to symmetric product-by-product input-output tables using the industry technology assumption and aggregated to a common 26-sector classification.[7] To establish concordance between the 26 sectors in the EORA database and the UN's commodity trade statistic database we rely on Engel (2016). Table A2 in the appendix gives information on the sectors covered in our final dataset and their concordance with the ISIC Rev.3 classification in our export dataset. Information to construct our proxy for disaster occurrence comes from five global climate models (GCMs) of the Coupled Model Intercomparison Project phase 5 ensemble (CMIP5, Taylor, Stouffer & Meehl 2012), which have been bias corrected within the Inter-Sectoral Impact Model Intercomparison Project 2A (ISIMIP2A, Hempel, Frieler, Warszawski, Schewe & Piontek 2013). Additionally, we use data from the emergency event database provided by the Center of Research on the Epidemiology of Disasters at the University of Louvain.[8] The emergency event database captures disaster events, for which at least one of the following criteria has been realized: (1) ten or more people died due to the disaster; (2) at least 100 people were affected; (3) a state of

[6] http://wits.worldbank.org/wits/

[7] Please see Lenzen et al. (2012), Lenzen et al. (2013) and https://worldmrio.com/eora26/ for a more detailed description.

[8] https://www.emdat.be/

emergency has been declared; or (4) a call for international assistance has been made. For each disaster the type, information on the number of fatalities, the total number of people affected, and the total amount of estimated direct damages in US dollars is reported in the database.

In Table 1 the number of observations per world region and sectoral group are shown. The manufacturing sector is in all world regions the sector where most countries are active each year, which is then followed by the agricultural sector. The energy sector is the least traded sector. All in all, Table 1 makes us confident that we have enough observations per country, sector and year to identify the impact of supply chain shocks on a country sector's export performance.

Table 1: Observations by region and sector

	Agriculture	Manufacturing	Energy	Mining	Total
Americas	1,931	3,861	284	1,290	7,366
Asia	1,718	3,423	277	1,129	6,547
Africa	2,959	6,015	324	1,994	11,292
Europe & Central Asia	3,029	6,162	857	2,051	12,099
Total	9,637	19,461	1,742	6,464	37,304

4.1 Supply chain connectivity

From EORA's 26 sector multi-regional input-output tables, we use values for the intermediate good sales between each sector and country, which contain both inputs sourced domestically and inputs sourced abroad. We, then, divide the intermediate good sales matrix by the total output of each sector. This gives us a so called technical coefficient matrix, A, where each column of this matrix represents an industrial recipe used to produce a single industry's good. Finally, the total, i.e., direct and indirect, amount of inputs used in one sector's production from all other sectors, is given by the Leontief inverse, which is calculated as

$$L = (I - A)^{-1}, \tag{2}$$

and summarizes the network effects generated when final output changes. Each element of the Leontief inverse, l_{hrt}, summarizes all direct and indirect effects created in sector h to supply a single unit of final demand for sector r in year t.

Using this framework, we are able to classify each country's sector according to its degree of spatial connectivity. Thereby, production of sector r can have two effects on the other sectors in an economy. If sector r increases its output, i.e., the demand will be increased from sector r for goods produced in other sectors $-r$ used as inputs to production. The degree of interconnection of sector r with those upstream sectors $-r$ from which it derives its inputs is called "backward linkage". Formally, it is given as

$$BL_{(agg)} = \frac{1'_r L_{rh}}{\frac{1}{n*m} 1_r L_{hh} 1_h}, \tag{3}$$

where n being the number of sectors and m being the number of countries. Increased output of sector r means that more goods produced by sector r are available as inputs to production for all downstream sectors. The term "forward linkages" measures the degree of interconnection of a sector with those sectors to which it sells its outputs.[9] It is given as

$$FL_{(agg)} = \frac{G_{hr}1_r}{\frac{1}{n*m}1_h G_{ij} 1_r}, \tag{4}$$

where G stands for the Goshian inverse, which is the transposed Leontief inverse and pictures a supply-side view of the input-output relationships. Both measures, $BL_{(agg)}$ and $FL_{(agg)}$ captures direct and indirect effects as well as intra- and interregional linkages. The larger $BL_{(agg)}$ and $FL_{(agg)}$ the stronger is a sectors degree of spatial connectivity. In Figure 1, we plot these measures of spatial linkages for each sector in our sample for six different points in time.[10] The y-axis depicts the degree of backward linkages and the x-axis the degree of forward linkages. Sectors, which are below one in both measures, are generally seen as independent and not strongly connected to other sectors. Sectors with a forward linkage measure, which is larger than one, can be classified as sectors, which are dependent on interindustry demand. Whereas, sectors with a backward linkage measure, which is larger than one can be classified as sectors, which are dependent on interindustry supply. Finally, sectors with both measures larger than one are seen as generally dependent and strongly connected to other sectors.

Overall, it can be seen that the majority of sectors are not strongly interconnected with other sectors domestically as well as internationally. However, overtime the number of sectors, which are depended on interindustry demand, supply or both is increasing.

4.2 Natural disaster data

To construct our natural disaster index, we use daily 2 meter air temperature and precipitation rate measures of the WATCH Forcing Data ERA-Interim (WFDEI, Weedon, Balsamo, Bellouin, Gomes, Best & Viterbo 2014) provided on a 0.5°× 0.5°regular latitude longitude grid. Climate extreme indices have been calculated using the ClimPACT2 package.[11] Only indices, which provide continuous information, in contrast to absolute indices based on day counts, have been used. An overview of used indices per disaster type is given in the Appendix in Table A3 and Table A4.

There is a large spatio-temporal scale gap between our different data sources, where input-output connectivity is measured at country-sector-year level and WFDEI data is based on daily temperature and precipitation values on a 0.5°× 0.5° regular latitude longitude grid. In the process constructing the natural disaster measure, we start using daily temperature and precipitation values of WFDEI to calculate monthly indices on the grid-point scale. In a next step, all grid points within a country's borders have been aggregated in three ways, the unweighted

[9] For an excellent introduction into input-output analysis see Miller & Blair (2009).

[10] The depicted number corresponds to the sector number as given in Table A2.

[11] This is a freely available R software package (https://github.com/ARCCSS-extremes/climpact2), which uses climdex.pcic and climdex.pcic.ncdf. It was developed by the Pacific Climate Impacts Consortium and its development was overseen by the World Meteorological Organisation's Expert Team on Sector-specific Climate Indices (ET-SCI).

mean, the minimum/maximum value[12], and a weighted mean based on the within country spatial distribution of population (GPWv3 2005). Then, we calculated for every country, i, and every month, m, standardized anomalies from the long term monthly mean between the years, t, from 1990 to 2015, which is given as

$$\gamma_{imt} = \frac{X_{imt} - \bar{X}_{im}}{\sigma_{im}}, \tag{5}$$

where X corresponds to the climate extreme index of interest. For some climate extreme indices we introduced additional conditions on the monthly values in order to prevent false detections in the subsequent analysis. This means that for all *coldwave* indices mean minimum temperature had to be below 0 °C and that for all *heatwave* indices mean maximum temperature had to be above 30 °C. For all *flooding* indices the maximum 1-day precipitation rate had to be at least 10 mm day^{-1}. And for all *drought* indices the respective SPI/SPEI had to be below -0.1. By this procedure we generated $N_{indices} \times N_{aggregations}$ datasets for every disaster index. In a next step, we generated a disaster time-series by selecting data values above a certain percentile threshold (p90, p95, p97.5 and p99). Finally, to select the indices, which best predict a potential disaster in a country, we calculated a score measuring the relative success rates in predicting disasters reported in the EM-Dat database published by the Centre for Research on the Epidemiology of Disasters (EM-DAT 2019).[13]

To estimate future natural disasters, we use temperature and precipitation data of five global circulation models (GFDL-ESM2M, HadGEM2-ES, NorESM1-M, IPSL-CM5A-LR and MIROC-ESM-CHEM) of the CMIP5 ensemble (Taylor et al. 2012) bias corrected within the ISIMIP2A project (data denoted ISIe in Hempel et al. 2013) for two emission scenarios[14]. Populations dynamics on the regular ISIMIP grid (0.5°× 0.5°, lat × lon) have been accounted for using GPWv3 (2005) for the observable past, and data from Jones & O'Neill (2016) for the future under the shared socioeconomic pathway 2 (SSP2). The percentile limits have been estimated over the period 1990–2015, using data of the CMIP5 models historic experiment until 2005 and the respective RCPs from 2006. Subsequently, disasters for future time periods have been obtained for monthly country values exceeding the respective percentile threshold. The monthly country disasters have been collapsed for each year and country, which results in the final yearly time-series.

Table 2 depicts for each disaster type the number of affected sectors for each country and year. On average 10 percent of all observations are either affected by a drought, heatwave,

[12] This is depending on which distributions tail we were interested in. For instance, minima values of mean minimum temperature were considered for coldwaves, whereas maxima values of mean maximum temperature were used for heatwaves.

[13] Table A4 in the appendix shows the best predictive indices and scores for the single disaster types. We do not use a disaster measure directly based on events reported in the EM-Dat database out of following reasons. First, as the focus of this analysis is based to predict future - climate change induced - impacts of disasters on a country's export performance, we would not be able to project future disaster based on EM-dat events, as the information of these events are mainly based on insurance claim reporting. Second, the EM-dat database itself recently came under some critique as the probability and quality of reporting is not independent of a country's level of economic development and is, therefore, susceptible to potential endogeneity issues.

[14] The emission scenarios used in this study are the representative concentration pathway 2.6 (RCP2.6) and RCP4.5, which represent greenhouse gas concentration trajectories based on a stringent (RCP 2.6) and intermediate (RCP 4.5) scenarios of climate futures.

Table 2: Summary statistics - Disasters

	Base Period			2020 – 2040		2041 – 2070		2071 – 2100	
	#Observations	Mean	St.dev	Mean	St.dev	Mean	St.dev	Mean	St.dev
Drought	37,304	0.093	0.290	0.438	0.491	0.472	0.491	0.471	0.491
Heatwave	37,304	0.097	0.297	0.441	0.484	0.532	0.478	0.538	0.480
Coldwave	37,304	0.114	0.319	0.052	0.218	0.043	0.196	0.042	0.194
Flashflood	37,304	0.103	0.304	0.238	0.425	0.246	0.430	0.249	0.432
Riverineflood	37,304	0.010	0.300	0.224	0.417	0.233	0.421	0.237	0.424

coldwave or flash-flood event. Only, riverine-floods with 1 percent on average happen less often. In the right panel of Table 3 the predicted natural disasters per disaster type and period are shown. The occurrence of nearly all disaster types increases in future, with the strongest increase in droughts, heatwaves and riverine floods.

4.3 Sectoral supply chain shocks

In a further step, we now combine the information of interindustry linkages and the occurrence of natural disasters (see Figure 1). Sectors, which are marked red, are sectors in countries a natural disaster, as determined by our natural disaster indices and as laid out in Section 4.2, has happened. In all years, sectors, which are strongly interdependent in the supply chain, i.e., sectors with a value above one in the forward- and backward linkage measures, are hit by natural disasters. These sectors, due to their spatial linkages, have a large potential to transmit natural disaster shocks to many other countries and sectors over the supply chain. Finally, the number of independent sectors hit by a natural disaster is increasing over time.

4.3.1 Supply chain shock index

Finally, to construct our measure of supply chain natural disaster shocks, we combine each element of our supply-chain connectivity matrix, L, with our measure of natural disasters as laid out in Section 4.2. For each sector, h, in country, i, the proportion of inputs potentially affected by natural disasters at year, t, is given as

$$SCS_{hit} = \sum_{j=1}^{J} \sum_{f=1}^{F} \frac{L_{jit}(f,h)}{L_{it}(h)} \times ND_{jt}, \tag{6}$$

where $f = 1, 2, \ldots, F$ is the domestic or imported input used in the production of country i's good h and $L_{it}(h)$ is the total per unit use of inputs in country i's sector h at time t. Our disaster index, ND_{jt}, is one, whenever country j is hit by a natural disaster, as determined by one of our disaster indices.[15] Equation 6 shows that the level of shock a country's sector receives depends on two factors: First, how strongly the sector is connected to each other sector at home and abroad. The stronger the interdependence the larger the transmission of a disturbance. And second, how many of its trading partners are hit by a natural disaster. This means that

[15]Potential disaster are heatwave, coldwave, drought, springflood and riverineflood (see Section 4.2).

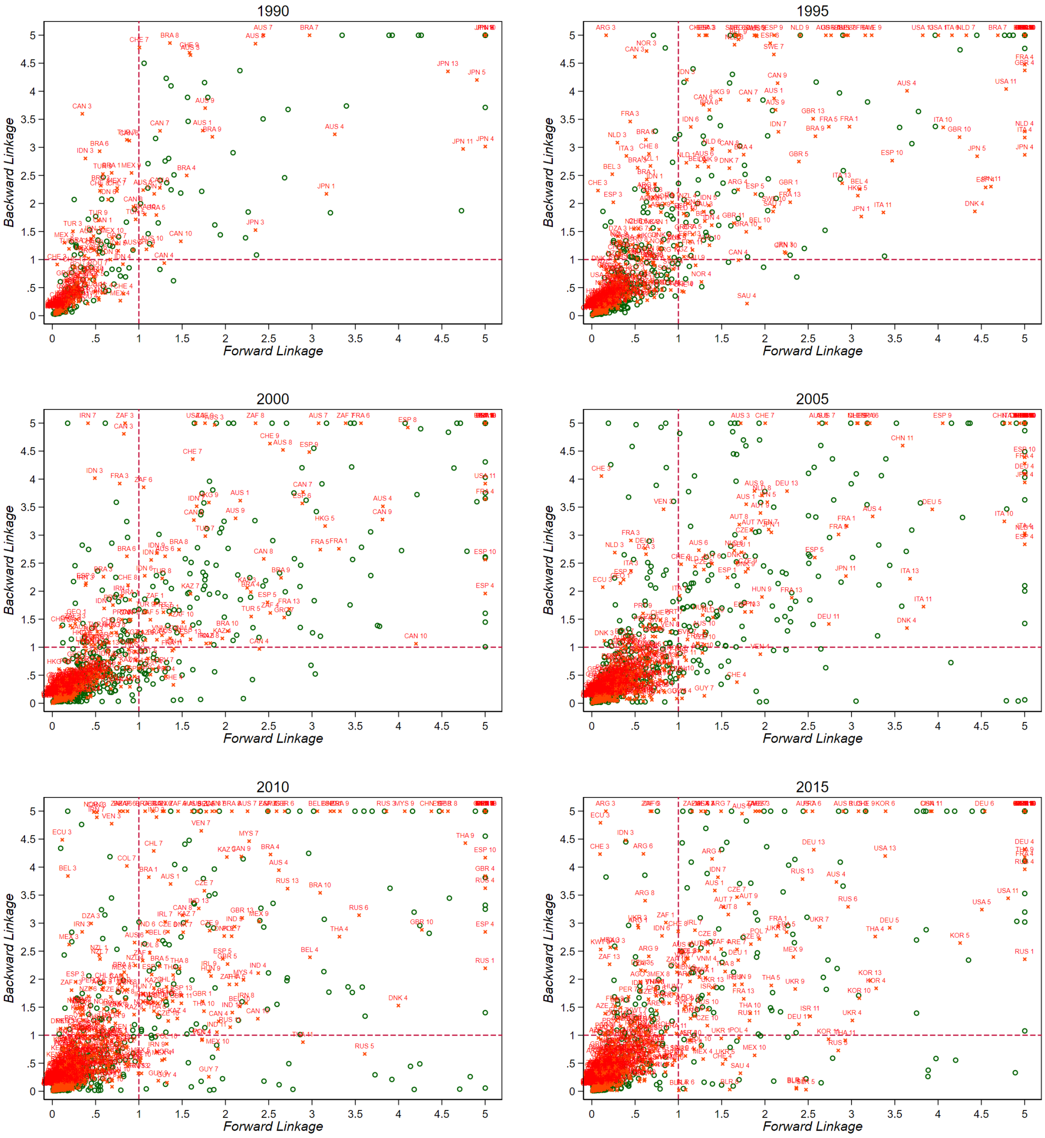

Figure 1: Sectoral forward and backward linkages and disaster shocks

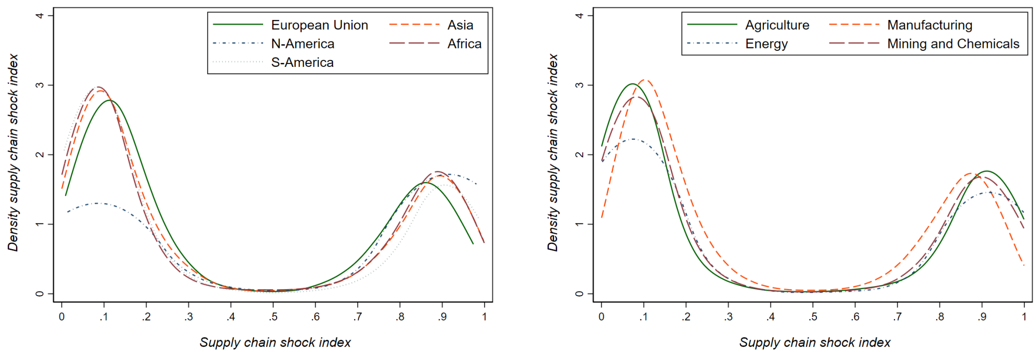

Figure 2: Distribution of supply chain shock index for different world regions (left panel) and different sectors (right panel)

a natural disaster, which hits only one sector, but this sector is strongly connected to sector h in country i, can have the same impact on sector h, as many sectors, which are hit by natural disasters, but which are not strongly connected to sector h.

The left panel of Figure 2 plots the distribution of the SCS index for different large regions in the world. Overall, the SCS measure of supply chain shocks features a bimodal distribution, with more of its density concentrated at the lower end of the support. The reason for this distribution lies in the general structure of intra- and intercountry supply chain linkages. In general, domestic inputs form the largest share in total inputs of a production process. Therefore, a disaster happening at home has not only a large direct impact on the sector itself, but also indirectly over the domestic supply chain (Kashiwagi et al. 2018). This leads to a larger value in the SCS index and explains part of the higher concentration of values at the higher end of the support. Whereas, inputs from abroad form a smaller share of total inputs in the production process and, therefore, disasters happening abroad will have a smaller value in the SCS measures and is part of the higher concentration of values at the lower end of the support.[16]

The bimodal distribution can be seen for all large regions in the world. However, in the European Union the mass of values in the lower and medium end of support is higher than for other regions. This can be explained that due to the single market and stronger export orientation countries in the European Union are more strongly interconnected, which means that these countries are more often receiving disasters happening abroad. Whereas, sectors in North America are receiving a large degree of inputs domestically, which explains the smaller mass of observation at the lower end of the support compared to the mass of observations at the higher end of the support.

The right panel of Figure 2 the SCS measure for sectors in all other regions is plotted. Interestingly, the manufacturing sector is the sector, which is particularly exposed to shocks in the supply chain happening abroad. This can be explained, that intermediate goods for the manufacturing sector are traded internationally and, in the last years in particular Asian countries have significantly gained in the market share of intermediate goods production, e.g., the production of inputs for consumer electronics in China.

[16]For more discussion on this distributional feature see Puzzello & Raschky (2014).

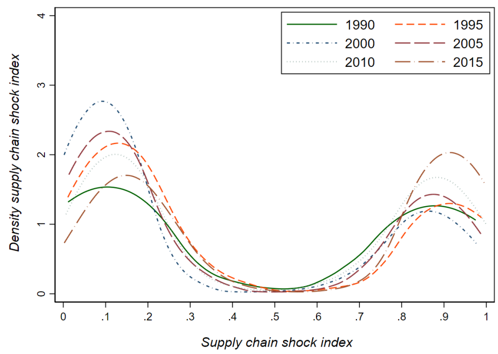

Figure 3: Distribution of supply chain shock index over time

Finally, in Figure 3 the change in the distribution of the SCS index over time is plotted. Overall, the bimodal distribution of the SCS measure can be found over the whole time frame of our sample with an increase in the values at the higher end of the support, which is explained by the increasing degree of input outsourcing over time and the increase in the occurrence of natural disasters.

4.3.2 Summary statistics

Table 3 depicts the summary statistics. For the econometric analysis, we dropped those observations, for which (i) no information on the quantity traded is available, (ii) that have insufficient variation after taking into account the country-year, country-sector, and sector-year fixed effects. The sample used to estimate the econometric model contains 37,265 observations. The sample covers 12 sectors from 172 countries around the world for the year 1990 to 2015.[17]

On average the value of a country's sectoral exports amounts to 5,761,478 US$ per year and is led by China, which has an average export value above 1 billion US$ in the "Electrical and Machinery" sector for the year 2013 until 2015. Our variable of interest, a sectoral productivity shock in a country due to disruptions transmitted over the supply chain, lies between 0 and 1 with an average value of 0.399 for a country, sector and year. The proxy for foreign competition, measured as output weighted disasters abroad per sector, country and year, varies between 0.061 and 0.824, where the maximum of a foreign competition shock is in the "Electricity, Gas and Water" sector in the year 1997. Finally, a sector's size and export experience might affect its ability to cope with a productivity shock transmitted over the supply chain. The gross output of a given sector, which serves as a measure of sectoral size, is led by China's "Electrical and Machinery" sector. Our measure of export experience, a country's sector exports relative to the world exports in the previous year, is on average 1% and lead by France's "Electricity, Gas and Water" sector, which had an export share of around 54% in the year 1996.

[17]For a detail list of countries and sectors covered see Table A1 and Table A2 in the appendix.

Table 3: Summary statistics

	Observations	Mean	St.dev	Min	Max
Dependent variable					
Export (in mill. USD)$_{hit}$	37,304	5.761	26.226	0.000	1070.248
Independent variables					
SCS index$_{hit}$	37,304	0.380	0.377	0.000	0.999
Competition$_{hit}$	37,304	0.476	0.162	0.059	0.824
(ln) Goutput$_{hit}$	37,304	0.310	2.576	-7.530	8.154
ExpShare$_{hit-1}$	34,113	0.009	0.025	0.000	0.542

5 The results

Table 4 presents the results, which are based on specification 1. Model (1) in Table 4 shows the outcome based on country-year and sector-year fixed effects. In all the other models (2-6) in Table 4 the results are based on the full fixed effect structure, including country-year dummies, country-sector dummies and sector-year dummies. Productivity shocks transmitted over the supply chain significantly reduce a sector's export performance. The country-sector specific control variables are as expected. A decrease in foreign competition, which is depicted with an increase in the $Competition_{hit}$ value, increases the export value. Larger sectors, measured by the gross output in that year, tend to export more. With including our full fixed-effect structure, as shown in column (2) of Table 4, the impact of productivity shocks transmitted over the supply chain becomes slightly smaller but remains statistically significant. A one standard deviation increase in the SCS measure decreases a sector's exports by around 11 percent. This is our preferred specification.

To ensure our estimated coefficients are not biased due to the omission of variables, which are correlated with the SCS measure and could influence the export performance of a country, in column (3) we include a sector's export share in the previous year as a proxy for experience. More experienced exporters may manage the supply chain more efficiently and, therefore, are able to switch to alternative suppliers in case the supply chain is hit by a natural disaster. Our parameter of interest, SCS$_{hit}$, remains robust in size and significance. In column (4) we use a stricter definition of the standard errors and cluster them at country-sector level. In column (5) we re-estimate specification 1 using a pseudo-Poisson maximum likelihood estimator as suggested by Silva & Tenreyro (2006), which is able to deal with 0 in the export variable and allows a more flexible treatment of the standard errors in regard with heteroscedasticity. Our estimate of the SCS$_{hit}$ impact stays robust. Finally, in column (6) we use an alternative definition of natural disasters, which takes the intensity of the natural disaster events into account.[18] Using a disaster intensity measure we find that a one standard deviation increase in the SCS measure decreases a sector's value of exports by around 13 percent.

[18]This means the ND_{jt} in equation 6 is the sum of the standard deviations for each index and country. In contrast, in our baseline definition ND_{jt} is just defined by dummy, which is 1 whenever a disaster occurred in a country.

Table 4: Estimation results - Supply chain shocks and a country's exports

	1	**2**	**3**	**4**	**5**	**6**
SCSindex_{hit}	−0.481*	−0.309**	−0.279**	−0.309**	−0.204***	−0.091**
	(0.268)	(0.136)	(0.126)	[0.143]	(0.057)	(0.038)
Competition_{hit}	3.762***	−0.199	1.072**	−0.199	−0.580**	−0.018
	(0.941)	(0.413)	(0.497)	[0.623]	(0.239)	(0.081)
(ln) Goutput_{hit}	1.278***	0.120*	0.068	0.120	0.221***	0.117*
	(0.019)	(0.066)	(0.065)	[0.119]	(0.038)	(0.066)
$\text{Exportshare}_{hit-1}$			12.810***			
			(0.817)			
Country-year FX	Yes	Yes	Yes	Yes	Yes	Yes
Country-sector FX	No	Yes	Yes	Yes	Yes	Yes
Year-sector FX	Yes	Yes	Yes	Yes	Yes	Yes
Observations	37,303	37,265	34,071	37,265	39,047	37,265
adj. R^2	0.744	0.935	0.941	0.935	0.938	0.935

Notes: Dep. Variable: (ln) export. In column (5) dependent variable export (in mill USD). *, **, *** indicate 10, 5, 1 % significance levels. Robust standard errors in parenthesis. In column (4) standard errors clustered at the county-sector level. In column (5) pseudo R^2 reported. In column (6) SCSindex based on intensity disaster measure. Constant included but not reported.

5.1 Sectoral decomposition

The effect of productivity shocks due to supply chain disruptions may be different for different sectors, e.g., the number and origin of inputs in the manufacturing sector may be different compared to the agricultural sector. Further, as we have seen in Section 4.3.1 the distribution of the SCS measure varies for different sector groups, and points to the potential internationalization of input sourcing in the manufacturing sector. Table 5 presents the results, when we re-estimate specification 1 for four large sector groups, i.e., the agricultural, manufacturing, energy and mining sector. Our estimates show that the negative effect of a supply chain shock on a sector's export value is mainly driven by the manufacturing sector. This is due to the different composition and number of inputs used in the production of the good being exported. The larger the number of inputs the higher the potential impact of supply chain shocks.

Table 5: Estimation results - Sectoral decomposition

	Agriculture	**Manufact.**	**Energy**	**Mining**
SCSindex_{hit}	−0.220	−0.589***	0.134	0.332
	(0.310)	(0.229)	(0.161)	(0.371)
Competition_{hit}	−0.381	0.031	−2.019*	2.337*
	(0.366)	(0.467)	(1.235)	(1.250)
(ln) Goutput_{hit}	0.076	0.394***	−0.039	−0.062
	(0.070)	(0.139)	(0.156)	(0.162)
Country-year FX	Yes	Yes	Yes	Yes
Country-sector FX	Yes	Yes	Yes	Yes
Year-sector FX	Yes	Yes	Yes	Yes
Observations	9,613	19,428	1,729	6,336
adj. R^2	0.955	0.952	0.763	0.935

Notes: Dep. Variable: (ln) export. *, **, *** indicate 10, 5, 1 % significance levels. Robust standard errors in parenthesis. Constant included but not reported. Sectoral composition stated in the appendix in Table A2.

5.2 Projections

We next turn to the impact of supply chain shocks on a sector's export performance taking future exposure to natural disasters due to climate change into account. To this end, we combine the estimated negative relationship between supply chain shocks and a sector's export performance with predictions about future climate change.

To predict supply chain impacts of climate change on a sector's export performance, we use the regression coefficient estimate based on specification 2 and the SCS measures based on natural disaster predictions for each global circulation models and the two emission pathways. We then calculate the predicted difference in the SCS measure for three future periods (2020–2040; 2041–2070; 2071–2100) and the baseline period (1990–2015) for each country and sector in our sample and multiply it by the estimated regression coefficient.

It has to be noted that these calculations are based on strong assumptions. While we allow for changes in the occurrence in natural disasters due to climate change and account for population dynamics in all predictions, we keep all other determinants, which could affect a sectors export performance, fixed to mean values over our sample period from 1990 to 2015. The input-output relationships to construct our SCS measure are based on the 2015 input-output network. Therefore, the predictions can be seen as upper limits of climate change impacts, in particular for the time periods further in future, if only very limited adaptation process takes place.[19]

The predicted impacts of climate change for the three future time periods (2020–2040; 2041–2070; 2071–2100) are shown in Table 6 and in Figure 4. All results have to be interpreted as mean annual change to the baseline period (1990–2015). Depending on the global circulation model and the representative concentration pathway additional supply chain impacts of climate change on a sector's export performance will be in the range of - 8% to -11% in the short-term period (2020-2040), -8% to -15% in the medium-term period (2041-2070) and -8% to -16% in the long-term period (2071-2100) with strong differences for the single country and sector, which can be seen at the minima and maxima values. The intuition behind the large differences for the single countries and sectors is the interdependence of a sector in the global production network as well as the exposure of its trading partners to natural disasters in the future. Figure 4 depicts the frequency distribution of the projected mean SCS impact of all five global circulation models considered for the three different time periods. It can be seen that with increasing climate change the distribution shifts to the left of the support, with its tails depicting an additional decrease in a sector's export of nearly 25%.

To account for not only the occurrence but also the intensity of future natural disaster, in Table 7 and Figure 5 we present predicted impacts of climate change for the three future time periods (2020–2040; 2041–2070; 2071–2100) using the intensity of natural disasters in the predictions. The supply chain impacts of climate change on a sector's export performance are large and will be in the range of -19% to -29% in the short-term period (2020-2040), -19% to -46% in the medium-term period (2041-2070) and -19% to -43% in the long-term period (2071-

[19]To account for potential adaptation measures, long-differences could be estimated. For a discussion on this issue see Dell, Jones & Olken (2014). However, as the time frame of our dataset is limited such an approach is unfortunately not feasible.

Table 6: Projected SCS impacts

		2020-2040				**2041-2070**				**2071-2100**			
		Mean	**SD**	**Min**	**Max**	**Mean**	**SD**	**Min**	**Max**	**Mean**	**SD**	**Min**	**Max**
RCP 2.6	GFD	-8.09	4.35	-24.26	14.43	-8.49	4.18	-22.62	15.49	-8.14	4.43	-23.71	18.13
	HAD	-13.29	3.40	-25.45	5.61	-13.79	3.69	-25.50	3.50	-13.76	3.72	-25.48	3.80
	IPS	-11.55	4.16	-25.38	7.99	-13.17	4.37	-25.44	2.58	-13.27	4.42	-25.41	1.65
	MIR	-11.34	3.85	-24.18	15.51	-13.25	3.71	-25.47	12.07	-13.41	3.79	-25.53	11.01
	NOR	-11.05	3.80	-25.23	10.15	-11.99	3.80	-24.62	9.37	-11.92	3.96	-26.04	6.04
RCP 4.5	GFD	-9.25	4.40	-24.30	12.49	-12.84	4.21	-25.46	5.39	-13.94	3.98	-26.05	3.11
	HAD	-11.49	3.82	-25.39	9.68	-15.19	3.30	-26.08	1.37	-16.11	3.24	-26.19	0.25
	IPS	-11.28	4.68	-25.36	7.98	-14.65	3.82	-26.06	3.26	-15.74	3.54	-26.18	4.01
	MIR	-10.78	4.13	-25.03	11.73	-13.53	3.67	-25.26	5.22	-14.96	3.45	-26.16	1.43
	NOR	-11.45	4.15	-23.92	10.91	-14.70	3.57	-25.82	1.40	-15.42	3.37	-26.08	-0.45

Notes: Predictions are based on the estimated regression coefficient SCSindex_{hit} from equation 2 of the baseline period (1990–2015). Abbreviations for global circulation models: GFD . . . GFDL-ESM2M; HAD . . . HadGEM2-ES; NOR . . . NorESM1-M; IPS . . . IPSL-CM5A-LR; MIR . . . MIROC-ESM-CHEM.

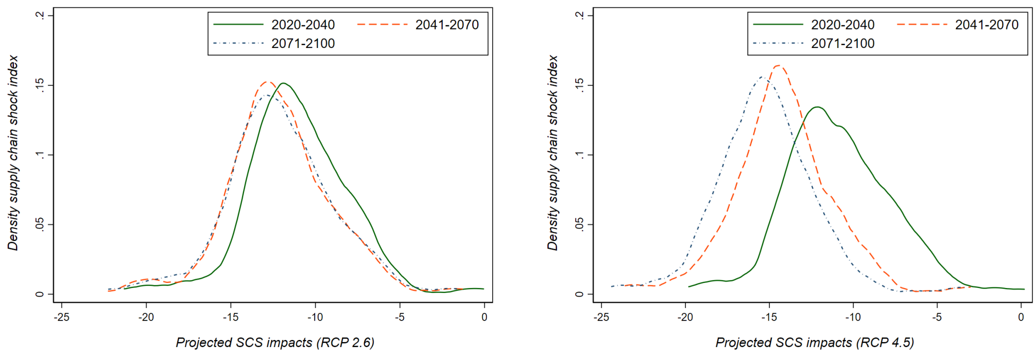

Figure 4: Distribution of projected SCS impacts for three different time periods. Left(right) panel represents impacts for RCP 2.6 (RCP 4.5).

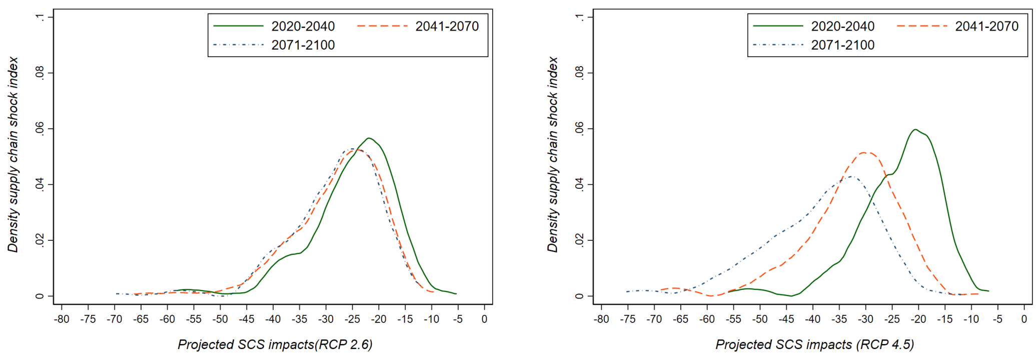

Figure 5: Distribution of projected SCS impacts (intensities) on exports for three different time periods. Left(right) panel represents impacts for RCP 2.6 (RCP 4.5).

2100). Again, very large differences between the single country and sector can be observed. In the frequency distribution of the projected mean SCS impact in Figure 5 it can be seen that with taking intensities of natural disasters into account the distribution shifts with increasing climate change significantly to the left of the support, with its tails depicting an additional decrease in a sector's export up to nearly 75%.

5.2.1 Country-specific projected impacts

As indicated in Table 6 there is a considerable heterogeneity in the strength of a supply chain shock on a sector's export value. The value of the SCS measure is determined by two factors - by the degree of connectivity between two sectors and if a sector is hit by a natural disaster. Therefore, the combination of a sector's trading partners in the supply chain and the change in the occurrence of natural disaster due to climate change determine the mean annual impact of our SCS measure for the future time periods considered in our analysis. Figure 6 shows the additional change in the average annual export value of a country for the RCP2.6 and the RCP4.5 scenarios, respectively. The predictions are based on the mean value of all five global circulation models. Thus, the country-specific predictions reported here represents the effect of country-level heterogeneity in the predicted changes in the natural disaster occurrence and

Table 7: Projected SCS impacts - Disaster Intensities

		2020-2040				2041-2070				2071-2100			
		Mean	**SD**	**Min**	**Max**	**Mean**	**SD**	**Min**	**Max**	**Mean**	**SD**	**Min**	**Max**
RCP 2.6	GFD	-18.85	10.53	-60.99	38.02	-19.24	11.85	-99.62	34.44	-19.45	9.37	-50.53	24.54
	HAD	-29.55	10.76	-72.44	32.40	-32.45	11.68	-73.82	4.33	-32.22	11.47	-70.06	16.86
	IPS	-29.52	13.89	-99.87	23.98	-46.07	17.35	-100.00	-6.28	-33.27	14.24	-93.70	18.17
	MIR	-26.18	11.12	-67.77	27.28	-31.96	12.22	-88.92	14.40	-32.33	12.87	-94.98	24.38
	NOR	-25.92	10.71	-66.52	15.89	-27.54	10.58	-70.38	12.02	-28.74	11.76	-78.20	15.99
RCP 4.5	GFD	-20.31	9.72	-57.96	21.21	-29.97	10.73	-60.76	24.64	-36.49	13.70	-99.66	0.20
	HAD	-24.86	10.38	-68.48	23.46	-35.22	11.80	-77.30	21.19	-42.84	13.44	-85.19	-12.85
	IPS	-29.52	13.89	-99.87	23.98	-46.07	17.35	-100.00	-6.28	-33.27	14.24	-93.70	18.17
	MIR	-23.39	10.96	-61.34	28.55	-31.52	13.32	-80.43	18.73	-36.49	14.48	-92.61	19.15
	NOR	-25.91	9.80	-60.22	13.30	-34.26	10.57	-69.69	2.11	-38.04	11.08	-75.74	3.84

Notes: Predictions are based on the estimated regression coefficient SCSindex_{hit} from equation 2 of the baseline period (1990–2015). SCSindex_{hit} is composed of input-output connections and the sum of natural disaster intensities in a country and year. Abbreviations for global circulation models: GFD . . . GFDL-ESM2M; HAD . . . HadGEM2-ES; NOR . . . NorESM1-M; IPS . . . IPSL-CM5A-LR; MIR . . . MIROC-ESM-CHEM.

its global production network. It does not account for possible heterogeneity in the historical relationship between a supply chain shock and average export value in a country. Plotting the average annual impacts over time gives an interesting picture for both RCPs. All countries' sectoral exports are negatively affected by climate change. However, the strongest effects can be found for countries in the tropics and sub-tropics as this is the region, which will observe strong adverse weather changes due to climate change, which are then transmitted over interregional supply chain connections. Table 8 lists the five countries with the strongest predicted impact, and the five countries with the weakest predicted impact for the three periods and 2 representative concentration pathways considered in the study. In both representative concentration pathways countries, which are less strongly hit by supply chain shocks in future, i.e., countries with a reduction in average export value between zero percent and 9 percent, are countries with a more localized production network, e.g., Afghanistan, or countries with a regionally concentrated production network in regions less affected by climate change, e.g., Slovenia, Island and Denmark. Whereas countries, which are situated in regions more strongly affected by climate change also have a stronger SCS impact on mean annual exports in future, which is a reduction between seventeen and twenty-four percent. These countries are, for example, Congo, Libya and Eritrea.

Table 8: Projected SCS impacts - Country specific impact

		2020-2040		**2041-2070**		**2071-2100**	
RCP 2.6	*Highest Impact*	Eritrea	-21.30	Eritrea	-22.27	Eritrea	-22.25
		Djibouti	-20.33	Djibouti	-20.23	Congo	-20.99
		Neth. Ant.	-19.25	Congo	-19.91	Libya	-19.75
		Libya	-18.64	Neth. Ant.	-19.82	Djibouti	-19.50
		Congo	-22.19	Colombia	-19.73	Neth. Ant.	-19.32
	Lowest Impact	Afghanistan	0.02	Afghanistan	-1.08	Afghanistan	- 1.42
		Bermuda	-1.10	Bermuda	-2.46	Bermuda	-2.68
		Georgia	-4.34	Island	-4.86	Georgia	-4.89
		Slovenia	-5.45	Slovenia	-6.00	Denmark	-5.00
		Island	-5.59	Denmark	-6.10	Island	-5.91
RCP 4.5	*Highest Impact*	Eritrea	-19.80	Eritrea	-23.61	Neth. Ant.	-24.42
		Djibouti	-19.59	Neth. Ant.	-23.24	Eritrea	-24.01
		Congo	-18.08	Djibouti	-22.34	Djibouti	-22.90
		Neth. Ant.	-18.07	Congo	-20.84	Congo	-21.57
		Libya	-17.45	Libya	-20.62	Libya	-21.36
	Lowest Impact	Bermuda	0.18	Afghanistan	-2.94	Afghanistan	-3.22
		Afghanistan	-0.51	Bermuda	-3.04	Bermuda	-3.87
		Island	-2.79	Island	-5.42	Island	-6.38
		Georgia	-3.16	Georgia	-7.96	Iraq	-9.00
		Slovenia	-4.53	Denmark	-8.03	Greenland	-9.00

Notes: Predictions are based on the mean of all five global circulation models considered. The upper panel shows the results for the representative concentration pathway 2.6 and the lower panel for the representative concentration pathway 4.5.

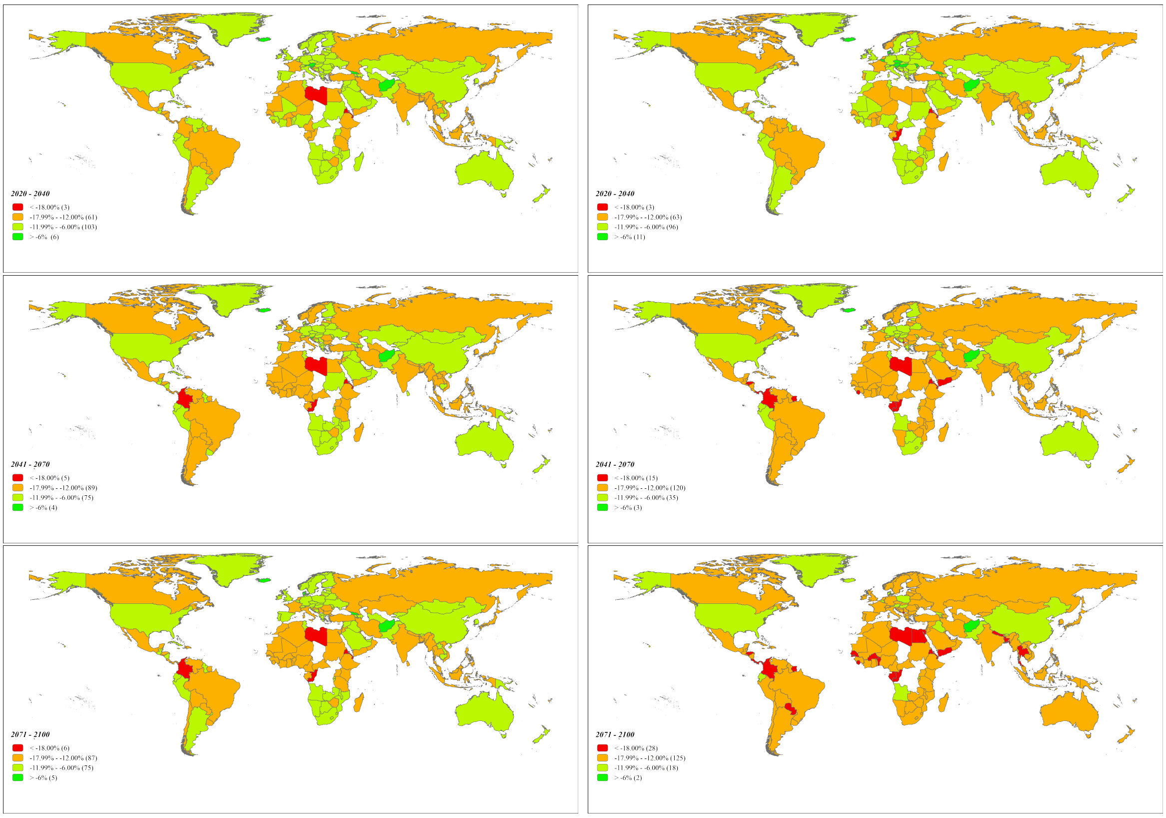

Figure 6: Predicted export change (mean over 5 global circulation models) - left panel (RCP 2.6); right panel (RCP 4.5)

5.2.2 Sector-specific projected impacts

The impacts of a climate change induced increase in supply chain shocks may differ across sectors because of different exposure to the global production network and the geographical distribution of climate change shocks. To explore heterogeneity across sectors Table 9 shows the mean, the minimum and the maximum value for each representative emission pathway for the twelve sectors considered in this study. It has to be noted that the outcomes in Table 9 are based on the regression coefficient of our SCS_{hit} measure for the whole sample, i.e., it represents a mean annual impact of a supply chain shock over all sectors in the baseline period. The combination of the input-output connections and natural disaster predictions are based on country-sector level. Alternatively, specification 2 could be estimated for each sector separately, which would allow to consider heterogeneous responses of each sector to supply chain shocks. However, given our stringent fixed effect structure unfortunately this is not possible for the individual sectors in our sample. That is a limitation and in interpreting the results in Table 9 the uniform sectoral response to shocks has to be considered. Thus, the sector-specific predictions represent the effect of country-level heterogeneity in the predicted changes in the natural disaster occurrence and the sectors role in the global production network.

On average the annual export value per sector over the whole time period, i.e., from 1920 to 2100, is additionally reduced by around 11 percent compared to the baseline period for the RCP 2.6 and thirteen percent for RCP 4.5 scenario. Within each sector the heterogeneity is large and economic significant, meaning that, for example, in the "Wood and Paper" sector Eritrea will have an additional average reduction of around twenty-two percent. Whereas, Afghanistan will have in the same sector no additional or even a slight decrease in the average negative impact for the same time period.

Table 9: Projected SCS impacts - Sectors

		RCP 2.6				RCP 4.5			
	C	**Mean**	**SD**	**Min**	**Max**	**Mean**	**SD**	**Min**	**Max**
Agriculture									
Agriculture	174	-11.78	3.28	-23.18	1.39	-13.48	3.27	-23.64	1.48
Fishing	169	-11.87	2.86	-22.75	-4.50	-13.51	2.86	-23.31	-3.83
Food & Beverages	173	-11.84	3.23	-22.73	1.42	-13.52	3.21	-23.21	0.01
Manufacturing									
Textiles & Wearing Apparel	173	-11.95	2.84	-21.73	-2.81	-13.57	2.82	-22.27	-3.08
Metal Products	171	-11.91	2.93	-22.13	-2.22	-13.55	2.91	-22.65	-2.41
Electrical and Machinery	171	-11.78	2.95	-22.63	-1.59	-13.41	2.93	-23.24	-1.70
Transport Equipment	169	-11.76	2.81	-22.05	-2.85	-13.40	2.82	-22.99	-3.09
Wood and Paper	172	-11.74	3.09	-22.31	1.38	-13.41	3.08	-22.82	-0.05
Other Manufacturing	172	-11.74	3.09	-21.68	1.11	-13.37	3.07	-22.23	-0.32
Mining and Energy									
Petro., Chem. & N-Metal. Min.	174	-11.83	3.02	-22.46	1.11	-13.46	3.01	-22.96	-0.30
Electricity, Gas and Water	136	-11.34	5.54	-24.29	6.61	-13.02	5.30	-24.88	2.75
Mining and Quarrying	173	-11.60	3.33	-22.35	0.84	-13.29	3.34	-22.88	-0.12

Notes: Predictions are based on the estimated regression coefficient SCSindex$_{hit}$ from equation 2 of the baseline period (1990–2015).

6 Conclusions

Today, the production of a final good in a country is based on numerous input-output interlinkages domestically as well as increasingly internationally. Disturbances in one country can be propagated over the supply chain leading indirectly to a change in other countries' macroeconomic outcomes. This paper addresses the impact of a natural disaster induced production shock, which can be transmitted over the supply chain - namely natural disasters. Combining a large dataset of input-output connections with a natural disaster dataset, we find that a one standard deviation increase in supply chain shocks decreases a sector's export by 11 percent. Further, we show that this negative effect is mainly driven by the manufacturing sector. Finally, predicting future supply chain shocks we find a potentially strong impact of climate change on the extend of the negative effects of supply chain shocks on a sector's export value. Although, the impact depends on the global circulation model in most of the cases it reduces exports and it is considerably large. Finally, the impact of climate change is heterogeneous between the countries and depends on the extend of a sector's global production network and the strength of increase in natural disaster in that region. Our results suggest, that it is countries in the tropics and subtropics, which will be particularly negatively affected by these shocks in future.

These findings are economic important. We show that countries, which are regularly hit by natural disasters are also strongly interdependent in global production networks. Regarding domestic disasters, policy makers need to the take the prevalent risk of supply chain disruptions due to natural disasters into account. At national level, pro-active measures, like zoning and building standards, could be implemented. Public information campaigns on disaster risk could incentivize private adaptation measures and insurance uptake. After a disaster has happened, financial disaster relief aid and solid financial institutions could speed up the disaster recovery period and decrease the length of the supply chain disruption. For disaster happening abroad, information campaigns could made companies aware of the potential risk of supply chain disruptions, which could incentivize companies, for example, to increase their level of geographical diversification in their global production network or intensify the use of storage facilities.

At the global level one major contributor to natural disaster occurrence is climate change. International coordinated policy, which reduces the amount of greenhouse gases, will also reduce the future risk of natural disasters and therefore, will decrease the potential negative impact of future supply chain disruptions.

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Appendix

A Tables

Table A1: Country composition

Country	Obs.	Country	Obs.	Country	Obs.	Country	Obs.
Afghanistan	33	Czech Republic	276	Laos	64	Russia	240
Albania	228	Denmark	312	Latvia	264	Rwanda	203
Algeria	284	Djibouti	11	Lebanon	217	Samoa	166
Andorra	206	Dominican Rep.	192	Lesotho	151	Sao Tome & Pri.	162
Angola	38	Ecuador	279	Libya	31	Saudi Arabia	273
Antigua	93	Egypt	253	Lithuania	264	Senegal	224
Argentina	276	El Salvador	261	Luxembourg	204	Serbia	240
Armenia	216	Eritrea	10	Macao SAR	213	Seychelles	205
Aruba	87	Estonia	252	Madagascar	286	Sierra Leone	41
Australia	312	Ethiopia	210	Malawi	272	Singapore	312
Austria	264	Fiji	160	Malaysia	310	Slovakia	261
Azerbaijan	230	Finland	312	Maldives	109	Slovenia	264
Bahamas	188	France	264	Mali	166	South Africa	288
Bahrain	179	French Polynesia	218	Malta	244	South Korea	301
Bangladesh	269	Gabon	173	Mauritania	78	Spain	311
Barbados	209	Gambia	206	Mauritius	256	Sri Lanka	249
Belarus	215	Gaza Strip	90	Mexico	312	Sudan	188
Belgium	252	Georgia	239	Moldova	229	Suriname	193
Belize	255	Germany	312	Mongolia	168	Swaziland	128
Benin	192	Ghana	187	Montenegro	116	Sweden	288
Bermuda	46	Greece	289	Morocco	259	Switzerland	312
Bhutan	127	Greenland	239	Mozambique	192	Syria	107
Bolivia	261	Guatemala	252	Myanmar	78	Macedonia	242
Bosnia & Herzeg.	156	Guinea	176	Namibia	192	Tanzania	216
Botswana	190	Guyana	205	Nepal	129	Thailand	308
Brazil	307	Haiti	85	Netherlands	288	Togo	222
Brunei	193	Honduras	223	Netherlands Ant.	44	Trinidad & Tob.	281
Bulgaria	236	Hong Kong	276	New Caledonia	179	Tunisia	284
Burkina Faso	208	Hungary	281	New Zealand	292	Turkey	308
Burundi	248	Iceland	290	Nicaragua	255	Turkmenistan	22
Cambodia	177	India	310	Niger	231	UAE	116
Cameroon	212	Indonesia	300	Nigeria	191	UK	275
Canada	312	Iran	156	Norway	276	USA	300
Cape Verde	144	Iraq	36	Oman	291	Uganda	261
Central Afr. Rep.	226	Ireland	285	Pakistan	146	Ukraine	240
Chile	294	Israel	242	Panama	228	Uruguay	263
China	288	Italy	263	Papua N. Guinea	88	Vanuatu	66
Colombia	292	Jamaica	257	Paraguay	300	Venezuela	217
Congo	118	Japan	296	Peru	260	Viet Nam	190
Costa Rica	251	Jordan	227	Philippines	220	Yemen	133
Cote dIvoire	239	Kazakhstan	191	Poland	264	Zambia	252
Croatia	286	Kenya	186	Portugal	310	Zimbabwe	184
Cuba	88	Kuwait	152	Qatar	155		
Cyprus	286	Kyrgyzstan	191	Romania	310		

Table A2: Sector composition

#	Sectorname	Obs.	ISIC Rev. 3 Sectors
1	Agriculture	3,281	01, 02
2	Electrical and Machinery	3,051	29, 30, 31, 32, 33
3	Electricity, Gas & Water	3,202	40, 41
4	Fishing	3,305	05
5	Food & Beverages	3,282	15, 16
6	Metal Products	3,262	27, 28
7	Mining & Quarrying	3,295	10, 11, 12, 13, 14
8	Other Manufacturing	3,250	36
9	Petroleum, Chemical & Non-Metallic	3,223	23, 24, 25, 26
10	Textiles & Wearing Apparel	3,168	17, 18, 19
11	Transport Equipment	3,243	34, 35
12	Wood & Paper	1,742	20, 21, 22

Table A3: Definition of indices.

Index	Description
PRCPTOT	Total wet-day precipitation
RX1day	Max 1 day precipitation
RX5day	Max 5 day precipitation
SPEI	Standardised precipitation evapotranspiration index (3,6,12 months)
SPI	Standardised precipitation index (3,6,12 months)
TNm	mean minimum temperature
TNn	Min TN
TXm	mean maximum temperature
TXx	Max TX

Table A4: Disaster types and final climate extreme indices.

Disaster	Index	aggregation	score	score XL	N	N XL
Coldwave	TNn	mean_uw	22.20	26.57	312	32
Riverine Flooding	RX5day	mean_uw	10.28	12.27	2214	519
Flash Flood	RX5day	maximum	8.37	11.01	579	92
Heatwave	TXx	mean_uw	22.30	23.60	152	25
Climatological Drought	SPEI3	minimum	12.16	10.87	387	283

Notes: The success rate score is calculated as $Score = \sum_p \frac{EMDat_{detected}}{N_{EMDat}} / \frac{N_p}{N}$ for $p \in [p90, p95, p97.5, p99]$.

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