The Transmission of Climate Shocks: The Case of Floods in India

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Abstract

This paper relates to a recent literature on the propagation of natural disasters through Input-Output linkages. We combine manufacturing data from the Annual Survey of Industries in India for the years 2000-2007 with the flood archive from the Dartmouth Flood Observatory, and apply the empirical strategy suggested by De Chaisemartin and d'Haultfoeuille [2022a]. Output and capital decrease after the first flood hits a district, especially in areas with the lowest historical exposure. This suggests that adaptation plays a role in mediating the impact of extreme weather events. We also find that manufacturing industries that rely on Agricultural inputs suffer a larger decrease in output and capital, and their output price increases, which provides evidence of a supply shock with persistent impacts. At the product level, we find some evidence of propagation through Input-Output linkages: when a high share of the production of a specific product is located in areas affected by extreme floods, establishments manufacturing the same type of product that are not directly affected experience an increase in the price and a decrease in the quantity produced.

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1 Introduction

As global warming has reached 1ºC above pre-industrial levels, there is a global consensus on the increased severity and intensity of extreme weather events Pörtner et al. [2022]. This increase in temperature and the damages induced by the natural disasters will impose some economic costs, which are still uncertain. Not only the direct damages are not precisely known by economists, but also the capability of markets to adapt is still on the process of being fully understood by researchers. In addition, these damages will be substantially higher in developing economies, both due to the higher exposure and higher vulnerability of their markets. One of the weather events that usually results in larger damages is floods.

This paper analyzes in detail the impact of floods in India, a country that is yearly exposed to this natural disaster, and in the particular setting of the manufacturing sector. Our first goal is to understand how floods directly affect local production and capital accumulation for different industries. In relation to the role of adaptation, we would also like to explore the consequences of floods for product quantity and price, to understand how the market is propagating or dampening the effect. In addition, we would like to understand whether there is any link between the location of products and the exposure to damages, as perhaps the incidence of repeated floods in a given location can shape the production across space.

With this purpose, we have built a panel of manufacturing establishments in India for the years 2000-2007, and we have merged it with flood data from the Dartmouth Flood Observatory, together with monthly rainfall data at the 0.5 $\times$ 0.5 degree resolution, from the *Terrestrial Air Temperature and Precipitation: 1900-2017 Gridded Monthly Time Series, Version 5.01*, compiled by Kenji Matsuura and Cort J. Willmott[1]. We can identify the location of the establishment, at the district level, which can inform us about its yearly exposure to floods. In addition, this extreme weather events have potentially heterogeneous impacts across different locations, as well as dynamic effects. Given the complicated setting, we apply the empirical framework recently developed by De Chaisemartin and d'Haultfoeuille [2022a], which is robust to heterogeneous and dynamic effects.

At the establishment level, we find that extreme weather events, and more specifically, severe-extreme floods have an adverse impact on establishment-level outcomes: total output falls, employment weakens, capital accumulation decreases, labor productivity shrinks and wages contract. More

[1] Available for download from http://climate.geog.udel.edu/~climate/html_pages/download.html

importantly, these effects seem to build over time and worsen across periods, as even four years after being initially exposed to an extreme-severe flood, affected establishments remain relatively worse, when compared to establishments that remain not exposed to these extreme weather events. Furthermore, we also document important degrees of heterogeneity in the impact of these events across the distribution of firms, as establishments in less previously exposed districts do relatively worse than establishments in districts with a history of being exposed to floods, pointing towards an important role for previous experiences, learning and adaptation measures, and also establishments in sectors closely related to agricultural inputs also suffer more, relative to sectors linked to construction or the transport industry.

In order to understand the mechanisms driving these different levels of heterogeneity we also explore disaggregated data at the product level and document that establishments in areas affected by extreme floods seem to suffer a supply shock: product value sold decreases, while the output price increases. Similarly to the establishment analysis, we find that these results are stronger for industries that purchase high amounts of inputs from the Agricultural sector.

Finally, we exploit the geographical variation of the product production and input usage data available in the Annual Survey of Industries. In this case, we restrict our analysis to products in unaffected locations, and compare their production decisions in years where their potential competitors, suppliers or customers are mostly located in districts affected by floods. We find that the share of competitors in flooded areas increases the output price and reduces the quantity produced and sold, while a higher share of customers located in flooded areas decreases the sale price. This suggests that the effects of floods are not limited to the area covered by the extreme weather event, as they affect product markets in other locations.

Related Literature

First, this work contributes to a branch of the literature that studies the impact of floods in production and decision-making. Recent research has combined detailed natural disaster maps with worldwide nightlight data to estimate the impact of floods in urbanization at high spatial resolutions. Kocornik-Mina et al. [2020] find that economic activity, proxied by nightlight, is reduced between 2% and 8%: the effect is mostly contemporaneous and stronger in low elevation areas, while they do not find any evidence of reallocation of activity within cities. Gandhi et al. [2022] find impacts on nightlight of similar magnitude, though their estimates are much higher in low income countries compared to high income. In addition, cities exposed to more floods in the past are less affected by current events.

For the U.S., Jia et al. [2022] focus on the increase in flood risk, which decreases firm entry and employment at the county level. They also highlight the importance of long run adjustments to risk by both firms and workers, compared to the direct impact of flood events. Another relevant mechanism with respect to flood risk is the role of transfers, as Pang and Sun [2022] provide a theoretical framework to show that the optimal transfer should factor in both damage and long run characteristics of a location. The role of expectations is also explored by Gallagher [2014], who suggests that households do not use all the available information when assessing flood risk, as they overreact to a flood event by increasing their insurance take-up.

Climate change is expected to increase the sea level, inducing coastal flooding in low elevation areas. This is the focus of Desmet et al. [2021], who incorporate the projections for global sea level rise into a dynamic geography model. Adaptation through the responses of investment and migration reduces the GDP loss from 4.5% to 0.11% in 2200. In addition, Balboni [2021] finds that the optimal infrastructure network in Vietnam would have achieved higher welfare gains, had it avoided low elevation areas exposed to coastal flooding. We plan to contribute to this literature by focusing on the impact of floods in the manufacturing sector of India, analyzing adaptation through production linkages in a developing economy.

Second, we contribute to a growing literature on the mechanisms that propagate or dampen the impacts of natural disasters and extreme weather events across space. Using firm network data, Carvalho et al. [2021] find evidence of downstream and upstream propagation of the 2011 earthquake to unaffected regions in Japan. In their quantitative model, the aggregate effect is more than twice as large due to the propagation of the shock to firms outside the affected area (0.47 % decrease in GDP, compared to 0.21 only locally). Boehm et al. [2019] study the impact of the same event on US multinationals owned by Japanese partners, finding important decreases in production and imports from the home country for these companies. The relevance of certain inputs when analyzing natural disasters is also studied by Barrot and Sauvagnat [2016], who find substantial downstream propagation of natural disasters in the US, especially for those inputs that are specific to a given supplier.

With respect to the dampening of the effects of extreme weather shocks, recent literature has identified different mechanisms. First, Albert et al. [2021] analyze how labor and capital flows react to droughts in Brazil, finding a decrease in capital inflows and an increase in migration from affected areas, though they also experience short run capital inflows. Second, Castro-Vincenzi [2022] found that the global car industry has chosen plant location and capacity to hedge against disruptions induced by floods. Third, Pankratz and Schiller [2021] use geolocalized supply chain data to document that suppliers of firms affected by extreme heatwaves or severe floods are more likely to stop trading. We would like to contribute to this literature by analyzing how product location changes across space, how it relates to the establishment industry and the differential impacts on price and quantity.

Finally, a strand of the literature on extreme weather events has focused on the case of India. From a corporate finance perspective, Rao et al. [2022] find that listed firms in India experience a decrease in capital and firm value if their sector is sensitive to excess rainfall, and that subsequent investment helps in the later recovery. For the agricultural sector, Jayachandran [2006] documents that higher rainfall is related to an increase in yield and agricultural wages. In a similar direction, Brey and Hertweck [2019] also suggest that droughts can decrease agriculture yield and wages. For the manufacturing sector, Somanathan et al. [2021] focus on the Annual Survey of Industries to find that labor productivity decerases and absenteeism increases in extreme hot days, while Pelli et al. [2022] find that output and capital decrease as a consequence of tropical cyclones, reallocating to better performing industries. Close to our setting, Hossain [2020] finds that establishments in the Annual Survey of Industries reduce their output and capital when they are affected by a flood, inducing reallocation of labor towards the informal sector. We would like to study as well the impact of floods in manufacturing, but focusing on the impact at the product level, which has not been analyzed in the literature.

2 Data

2.1 Panel of manufacturing establishments

To analyze the impact of floods on firm-level performance, we rely on the Annual Survey of Industries (ASI) data which is the most comprehensive panel available for the registered manufacturing establishments in India. The ASI is a Government of India census of large plants and a random sample of about one-fifth of smaller plants registered under the Indian Factories Act. Large plants are defined as those employing more than 100 workers. The ASI provides a representative sample of all registered manufacturing establishments in India, with large establishments covered every year, and smaller establishments covered on a sampling basis. The basic unit of observation in the ASI is an establishment (called a factory in the ASI data).

The ASI cross-sectional data have district identifiers, which allow us to assign each plant to one district in India. However, the panel data does not contain those identifiers. To deal with this shortcoming, we follow Martin et al. (2017), who integrate district identifiers into the ASI panel by merging both cross-section and panel ASI datasets. We use the ASI data for the period of 2000-01 through 2007-08 based on the availability of said identifiers. The ASI provides annual data on establishments total output, the value of fixed assets, debt, cash on hand, inventories, input expenditures, the employment of workers and management, among several other variables.

Our main variables of interest are total output, capital, employment, wages,and labor productivity. Total output comprises total ex-factory value[2] of products and by-products manufactured as well as other receipts such as receipts from non-industrial services rendered to others, work done for others on material supplied by them, value of electricity produced and sold, sale value of goods sold in the same condition as purchased, addition in stock of semi- finished goods and own construction. Capital is measured as the depreciated value of fixed assets owned by the factory (i.e., land, building, plant, machinery) as on the closing day of the accounting year. Total employment of the establishment is measured as the average number of total persons employed in a given year[3]. We divide the total compensation paid to employees by the average number of employees to construct a measure of wages. We also measure labor productivity as total output divided by the number of employees. Furthermore, establishments report products in the ASI survey using ASI Commodity Classification (ASICC) codes. This will be extremely useful for our analysis at the product level. In addition, for every product produced by the establishment, we observe product sales value and quantity sold and effectively manufactured.

Across the years, the Government of India has split district and regions into smaller units. Industry

[2]The ex-factory value of all products and by-products manufactured is attained at the rate of net sale value (inclusive of subsidies etc.) with respect to each of the items.

[3]Total persons employed is defined to include all persons employed directly or through any agency (workers), persons receiving wages and holding supervisory or managerial positions engaged in administrative office, store keeping section and welfare section, and all working proprietors and their family members who are actively engaged in the work of the factory even without any pay and the unpaid members of the co-operative societies who worked in or for the factory in any direct and productive capacity

classification also changed across the years (from NIC 1998 to NIC 2004 to NIC 2008). To keep the geographic identifiers and industry classifications consistent across years, we follow the industry and district concordance table provided by Martin et al.(2017), and end up with 478 constant-boundary districts for which there is at least one firm located within the period of study.

2.2 Floods

We obtain information about worldwide historical floods from the *Global Active Archive of Large Flood Events* by the Dartmouth Flood Observatory (DFO) which uses different sources, such as news, governmental statements, satellite imagery, and remote sensing, to create and update the Archive. Each entry in the Archive is associated with a related "area affected" map outline representing a discrete flood event. We use these maps to perform a geospatial join and assign each flood event to one or several districts in India. Furthermore, for each flooding event, the database collects information about estimated dates for the start and the end of the event, the causes of the flood, an estimate of the geographical location and extent of the flood, and some measures of severity and overall damage. This archive starts in 1985 and is actively maintained. In this paper we focus on the most devastating flood events, which have the most important economic impacts. Hence we use DFO's severity scale (which ranges from 1 to 2, in increasing steps of 0.5) and focus on what we have called **severe** and **extreme floods**, which are events that have:

1. **Severe floods (Severity = 1.5)**

    - Greater than 2 decades but less than 100 year estimated recurrence interval (worldwide), AND/OR

    - A local recurrence interval of 1-2 decades and affecting a large geographic region (> 5,000 sq. km)

2. **Extreme floods (Severity = 2)**

    - An estimated recurrence interval (worldwide) greater than 100 years.

Given this classification of floods by their severity, we further define an extensive and intensive margin to measure the impact of floods of these characteristics across Indian districts. For the extensive margin, we define a set of dummy variables that take the value of one if at least one severe or extreme flood (severity 1.5 or severity 2) covers more than 50 percent (100 percent) of the area of a given district in a given year, and zero otherwise. We then assign this treatment to each firm given their location, such that all firms in a given district have the same value of treatment. In terms of the intensive margin, we define another set of variables that take as value the number of severe or extreme floods that hit a district in a given year and respectively cover more than 50 percent (100 percent) of the total district area. With these definitions in mind, we end up analyzing the impact of 15 severe/extreme floods in India, between 2000 and 2007.

In terms of the geographical distribution of floods, both during our sample period, but also at the historical level, Figure 1 displays district-level exposure of these extreme weather events. The top row deals with the exposure to all types of floods, while the bottom row focuses on severe and extreme floods, as defined previously. It seems like both the northeast region and the western region of the country are the most hit by extreme and severe floods during our sample period, whereas in the past both the north and south of the country also experienced these wrecking weather events. We will exploit this geographical variation in our event study design.

2.3 Weather data

Our primary source for climate data is the *Terrestrial Air Temperature and Precipitation: 1900-2017 Gridded Monthly Time Series, Version 5.01*, compiled by Kenji Matsuura and Cort J. Willmott[4]. This dataset provides worldwide (terrestrial) monthly mean temperature and precipitation data at 0.5 x 0.5 degree resolution (approximately 56km x 56km at the equator), where the grid nodes are centered on the 0.25 degree. We use geospatial software to aggregate the weather data to the district-month level, and further calculate average rainfall for each district during the year, during the Monsoon season, which generally takes place between June and September, and a measure of extreme rainfall, computed as deviations during the year and during the Monsoon season, from a historical rainfall average for each district.

2.4 Input-Output data

Finally, we explore the Input-Output linkages of the manufacturing establishments with the rest of the Indian economy. With this purpose, we use the 2000 Input-Output table from the Asian

[4] Available for download from http://climate.geog.udel.edu/~climate/html_pages/download.html

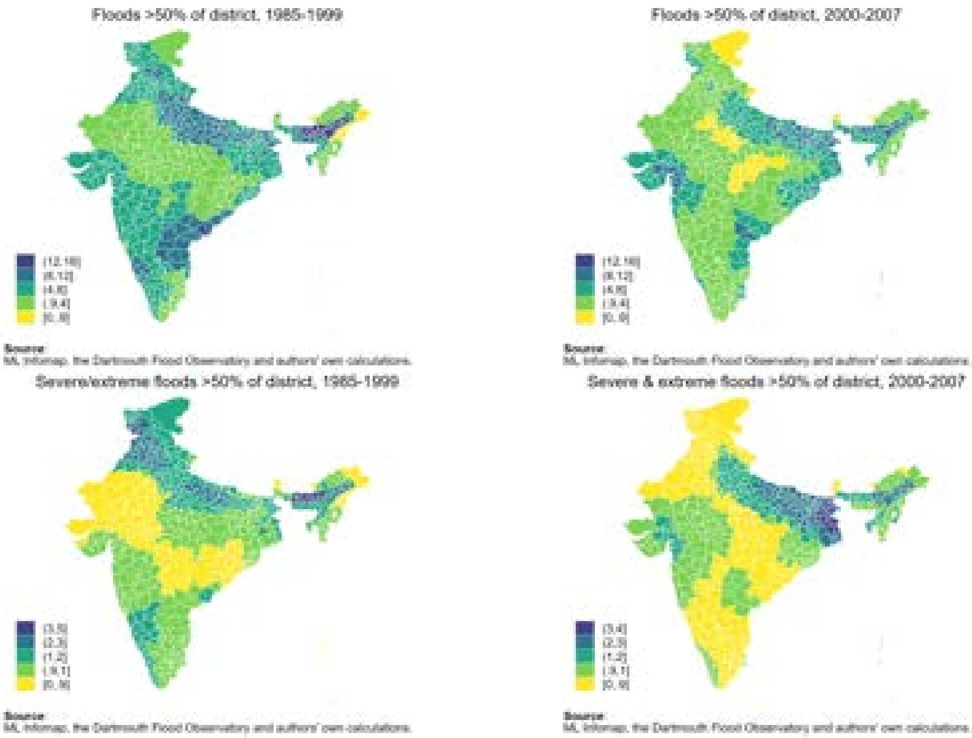

Figure 1: Exposure to floods in Indian districts across the years: All floods and only severe/extreme floods

Development Bank, which provides the input usage across 35 main sectors. The Annual Survey of Industries contains establishments from the 14 manufacturing sectors in the Input-Output table, which comprise broad industries such as "Food" or "Machinery". We merge this data by sector, and use the Input-Output table to explore the heterogeneity of the flood impact depending on the linkage of a particular manufacturing industry to other activities in the Indian economy, mainly Agriculture or Construction.

3 Empirical analysis: Manufacturing Establishments

3.1 Descriptive statistics

Table 1 reports the mean and standard deviation of our main variables of interest, namely our measures of establishments-level total output (y), labor input (l), capital accumulation (k), labor productivity (lp) and wages (w) across all years, for firms both in districts affected by severe and/or extreme floods covering more than 50% of the district's total area in any year of our sample (according to our definition of the extensive margin in the previous Section) and in districts not affected. The last two columns also show the t-statistic of a mean-comparison t-test between the two groups:

	(1) S/E Flood		(2) No S/E Flood		(3) Diff.	
	Mean	SD	Mean	SD	b	t
y	16.99	2.29	16.91	2.23	-0.08***	(-5.86)
l	3.95	1.49	3.98	1.46	0.03**	(3.15)
k	15.28	2.63	15.29	2.61	0.01	(0.41)
lp	13.04	1.48	12.93	1.47	-0.11***	(-12.20)
w	10.54	0.85	10.53	0.82	-0.00	(-0.45)
Annual rain (mm.)	1494.85	849.63	1213.26	773.73	-281.59***	(-54.48)
Monsoon rain (mm.)	1187.10	667.22	839.05	647.65	-348.05***	(-85.09)
Observations	31,119		202,001		233,120	

Table 1: Summary statistics: Firms in districts affected or not by severe/extreme floods

Only 13.34% of establishments are affected by either severe and/or extreme floods during our period of analysis, which seem to statistically differ in their lower employment, but interestingly, higher labor productivity and total output. It is worth noting that for firms in districts affected by severe or extreme floods the standard deviations associated to all the variables of interest are also larger, pointing towards a larger heterogeneity within this group. Furthermore, establishments in districts in which these types of floods cover more than 50 percent of the total area experience on average around 350 mm. more rain during the monsoon season.

3.2 Estimation strategy

Our identification strategy aims to exploit the different degrees of establishment exposure to and intensity of severe and/or extreme floods at the district level in different years. A popular method to estimate the causal effect of these types of "treatments" on an outcome is to compare over time groups experiencing different evolutions of their exposure to treatment, which is commonly referred to as the generalized differences-in-differences approach. In practice, this idea is implemented by regressing Y_{gt}, the outcome in group g and at period t , on group fixed effects, period fixed effects, and D_{gt}, the treatment of group g at period t.

Such two-way fixed effects (TWFE) regressions are probably the most commonly used technique in economics to measure the effect of a treatment on an outcome. Furthermore, motivated by the fact that in the two-groups and two-periods design, the differences-in-differences (DID) estimator is equal to the treatment coefficient in a TWFE regression, researchers have also estimated TWFE regressions in more complicated designs with many groups and periods, variation in treatment timing, treatments switching on and off, and/or nonbinary treatments. However, recent research has shown that in those more complicated designs, TWFE estimators are unbiased for an ATE only if parallel trends hold, there are no anticipation effects and if another assumption is satisfied: the treatment effect should be constant, between groups and over time. Unlike parallel trends, this last assumption is unlikely to hold, even approximately, in most of the applications where TWFE regressions have been used (De Chaisemartin and d'Haultfoeuille [2022b]). This realization has spurred a flurry of methodological papers diagnosing the seriousness of the issue, and proposing alternative estimators.

In our particular setting, besides the usual identification assumptions of no anticipation, treatment exogeneity and parallel trends, there are several concerns we need to deal with. In the first place, the nature of our treatment: the usual assumption in the DID literature is that there is a binary treatment that is adopted at a particular date and remains on afterwards. In our case this is not necessarily the case, as districts that might be affected by extreme-severe floods (i.e. treated) during a certain year do not need to be affected in the following year(s) as well; that is, our treatment is not absorbing: units can enter and exit treatment multiple times. Furthermore, other two concerns are related to the characteristics of the treatments. The treatment effects of floods are potentially heterogeneous both across time of the treatment (as different districts, and hence establishments, "enter the treatment" at different moments in time) but also potentially across cohorts: it may not necessarily be the case that the average effect of receiving a flood is the same for units receiving it sooner that later in the sample. Lastly, we can not rule out dynamic effects of the treatment, that can both increase or decrease over time.

To address these concerns, we follow Castro-Vincenzi [2022], who deals with a similar setting to ours, and employ the estimator suggested in De Chaisemartin and d'Haultfoeuille [2022a]. This is a differences-in-differences estimator of contemporaneous and dynamic treatment effects, robust to heterogeneity, that allows for the treatment to vary over time. The authors' main idea is to propose a generalization of the event-study approach to such designs, by defining the event as the period where a group's treatment changes for the first time. Their estimator of the expected difference between group g's actual outcome at time $F_g - 1 + l$ and its counterfactual "status quo" outcome if its treatment had remained equal to its period-one value from period one to $F_g - 1 + l$ is given by:

$$DID_{gl} = Y_{gF_g-1+l} - Y_{gF_g-1} - \frac{1}{N^g_{F_g-1+l}} \sum_{g':D_{g'1}=D_{g1}, F_{g'}>F_g-1+l} (Y_{g'F_g-1+l} - Y_{g'F_g-1}) \tag{1}$$

where Y_{gF_g+l} corresponds to the outcome of interest for group g at moment $F_g - 1 + l$, or l periods after group g received the treatment for the first time in period F_g, Y_{gF_g-1} corresponds to the same outcome of interest for group g one period before it changes treatment status for the first time, and $N^g_t = \#\{g' : D_{g'1} = D_{g1}, F_{g'} > t\}$ is the number of groups g' with the same period-one treatment as g, and that have kept the same treatment from period 1 to t. Intuitively, this DID estimator compares the $F_g - 1 - to - F_g - 1 + l$ outcome evolution of group g to that of groups with the same baseline treatment ($D_{g'1} = D_{g1}$), and that have kept that treatment from period 1 to period $F_g - 1 + l$, that is, l periods ahead after their initial treatment period F_g.

Moreover, De Chaisemartin and d'Haultfoeuille [2022a] also define the estimator of the event-study effects as:

$$DID_l = \frac{1}{N_l} \sum_{g:F_g-1+l \leq T_g} S_g DID_{gl} \tag{2}$$

which aggregates the DID_{gl} estimates, and where T_g denotes the last period where there is still a group with the same period-one treatment as group g and whose treatment has not changed since the start of the panel, $N_l = \#\{g : F_g - 1 + l \leq T_g\}$ is the number of groups for which DID_{gl} can be estimated, and $S_g = 1\{D_{gF_g} > D_{g1}\} - 1\{D_{gF_g} < D_{g1}\}$ is equal to 1 (resp. -1) for groups whose treatment increases (resp. decreases) at F_g. Intuitively, this estimator of the event-study effects represents an average effect of having been exposed to a weakly larger dose for l periods.

To fix ideas, in our specific setting, each group g corresponds to a given district (set of districts) that change status in their treatment for the first time at year F_g, as the treatment (incidence of extreme and severe floods) is assigned at the district level. Importantly, we want to analyze outcomes which are at a more disaggregated level than the level at which the treatment is assigned (establishment-level outcomes and district-level floods). Fortunately, the `did_multiplegt` command that implements the estimators proposed in De Chaisemartin and d'Haultfoeuille [2022a] can be used with data at a more disaggregated level than the (g, t) level, as it aggregates the data at the (g, t) level internally. Furthermore, when provided with data at a more disaggregated level than the (g, t) level, the `did_multiplegt` command automatically weights (g, t) cells by their number of observations in the data.

3.3 Establishment-level outcomes

3.3.1 Baseline results

We start by estimating the effect of the occurrence of a severe-extreme flood in the district where an establishment is located on its total output produced, employment, capital accumulation, labor productivity and wages. In first place, to be sure we are using the correct control group for our comparisons, we eliminate from the estimation all firms which suffered floods both at period 1 during our sample (2000), as well as during 1999 and 1998. This to ensure that we are indeed using as comparison groups establishments with the same baseline treatment, and that we can analyze our estimates as the effect of being exposed to extreme-severe floods versus the counterfactual "status quo" of not being exposed.

To the right of zero, the green line on Figure 2 below shows the DID_l estimates of the effects of a first extreme-severe flooding episode on the logarithm of total output, employment, capital accumulation, labor productivity and wages of affected establishments, the year of the first flood ($l = 0$), and in later years ($l > 0$). For total output, DID_0^y = -0.053 (s.e.=0.048): in the year of the first extreme-severe flooding event, total output fell by 5.3% more for establishments that were exposed than in establishments that were not. The effect, however, is statistically insignificant at the 10% level (t-stat=1.14). Furthermore, this effect builds up over time, and increases in magnitude up to 4 years after the initial flooding event, but the confidence bands, estimated using 100 bootstrap replications clustered at the district level, are also large. To the left of zero, placebo estimates are shown. The DID_l estimators control for state-specific linear trends: without them, placebos are large and significant. This lends credibility to the parallel trends assumption, at least over a few years De Chaisemartin and d'Haultfoeuille [2022a].

Regarding the other outcomes of interest, DID_0^l = -0.025 (s.e.=0.027), DID_0^k = -0.057 (s.e.=0.040), DID_0^{lp} = -0.030 (s.e.=0.020), and DID_0^w = -0.023 (s.e.=010): in the year of the first extreme-severe flooding event, employment fell by 2.5%, capital accumulation decreased by 5.7%, labor productivity dropped by 3% and wages shrank by 2.3% more for establishments that were exposed than in establishments that were not. These effect, however, are only statistically significant at the 5% level for the case of wages (t-stat=2.32). These results all correspond to the case when we use

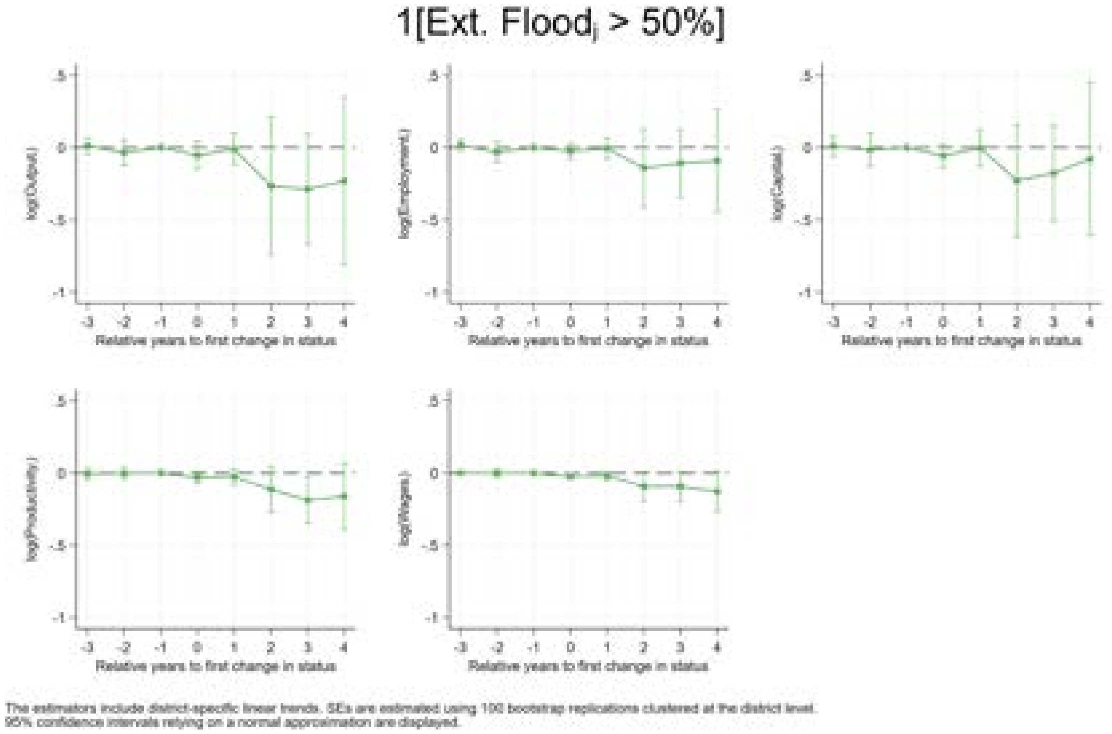

Figure 2: Effect of severe-extreme floods on establishment-level outcomes

the measure of the extensive margin as our treatment: a dummy variable that takes the value of one if at least one severe or extreme flood (severity 1.5 or severity 2) covers more than 50 percent of the area of a given district in a given year, and zero otherwise. However, the results are robust when using any of the other three measures defined in Section 2.2.

Importantly, the green lines on Figure 2 validate the research design, by showing that differential pre-trends are much smaller than differential trends after a treatment switch. They also shows that being exposed to a weakly higher number of extreme-severe floods for $l + 1$ periods has a negative effect on establishment-level outcomes, and that this effect is increasing with l. However, the DID_l estimates cannot be interpreted as effects per flood event, first because our measure of treatment is binary, but, most importantly, because they do not take into account further changes in treatment that occur after the first change in treatment status. Rather than estimating separately the effects of those subsequent changes in treatment status, which would require imposing restrictions on the dynamic effects of initial extreme weather events, this approach estimates the combined effects of initial and subsequent floods on the full outcome path De Chaisemartin and d'Haultfoeuille [2022a].

3.3.2 Firms in the census

The results from the baseline specification, summarized in the previous section, point towards a negative effect of sever-extreme floods over establishment-level outcomes: in the year of the first extreme-severe flooding event, at which an establishment changes treatment status for the first time, total output, employment, capital accumulation, labor productivity and wages fall more for establishments that were exposed to the treatment, in comparison to establishments that were not. These results also show that being exposed to a weakly higher number of extreme weather events for $l + 1$ periods has a negative effect on these outcomes, and that this effect is increasing with l. However, as also noted in the previous section, these estimates are statistically insignificant, at least in the case of total output, capital accumulation and employment across all horizons.

To explore the robustness of these results we turn to the estimation of this effects on a sub-sample of the whole panel of manufacturing firms. As mentioned in Section 2, the ASI provides a representative sample of all registered manufacturing establishments in India, with large establishments covered every year, and smaller establishments covered on a sampling basis. In practice, this means that the sampling design is composed by two different schemes: the *census* scheme and the *sample* scheme. Registered factories with over 100 workers (the "*census* scheme") are surveyed every year,

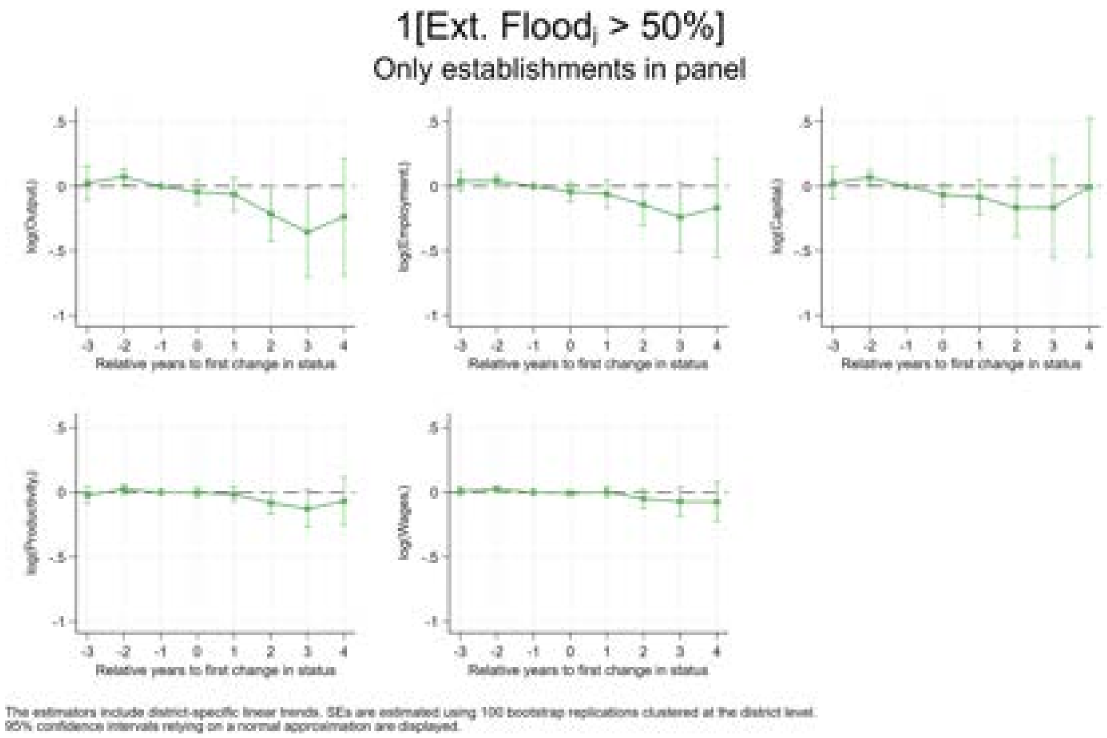

Figure 3: Effect of severe-extreme floods on establishment-level outcomes: Only firms in *Census*

while smaller establishments (the "*sample* scheme") are typically surveyed every three to five years. Moreover, the selection into the "*sample* scheme" is primarily random, and the survey provides sampling weights that allow the construction of representative samples at the state-by-industry level. Thus, the fact that an establishment disappears in a certain year from the "*sample* scheme" could be completely exogenous, but it may also be the case that it is related to the incidence of extreme-severe flooding events that have affected it during the year in course. In that sense, we would be under-estimating the overall effect of floods on establishment-level outcomes, as possibly firms that were the most affected could exit the "*sample* scheme" and would not report their data in the years following[5].

For that reason, we re-estimate the baseline specification, this time only for the firms in the "*census* scheme", that is the ones that are surveyed every year, and results are reported in Figure 3. The results resemble the ones from the baseline specification, both in terms of signs and magnitudes, but

[5]Currently, our data cleaning procedure excludes observations in which establishments are flagged as closed from the main regressions.

they are now statistically significant in most cases. For total output, DID_0^y = -0.045 (s.e.=0.049): in the year of the first extreme-severe flooding event, total output fell by 4.5% more for establishments in the "*census* scheme" that were exposed than in establishments that were not. As it was the case for the baseline specification, this effect builds up over time, and becomes significant at the 5% level after two years (DID_2 = -0.215, s.e.=0.107) and after three years (DID_3 = 0.356, s.e.=0.176). The results for the other outcomes of interest are very similar: DID_0^l = -0.042 (s.e.=0.038), DID_0^k = -0.066 (s.e.=0.044), DID_0^{lp} = -0.002 (s.e.=0.020), and DID_0^w = -0.007 (s.e.=011). As it was the case for output, these effects build up over time and become statistically significant at the 10% level after two years, in the case of employment, labor productivity and wages. This evidence points towards a delayed and somewhat persistent effect of extreme flooding events on establishment-level outcomes, specially for larger firms, included in the "*census* scheme".

3.3.3 Heterogeneity in previous exposure to floods

In this section, we further explore another dimension of heterogeneity across establishment in our data: their previous exposure to floods. This dimension might shape the way in which establishment-level outcomes react to the incidence of a severe-extreme flood, the intuition being that establishments located in districts which have experienced more frequent flooding events in the past might have developed some coping mechanisms over time, opening a window for adaptation efforts to deal with the impacts of flooding. On the other hand, districts less used to floods in the past might be less prepared to deal with the devastating effect of these extreme weather events, and might suffer larger losses and damages from the impact of severe or extreme floods in their territories.

In order to explore this argument, we rely on extended information from the Dartmouth Flood Observatory, from which we are able to retrieve information on floods not only for our period of analysis, but also back until the year 1985. With this information in hand, we compute two district-level measure of previous exposure to floods, defined as the total number of floods, i) of any severity type, and ii) of severity ≥ 1.5 (that is, severe and extreme floods), covering more than 50 percent of a given district area in a given year, between 1985 and 1999. Furthermore, we define a dummy variable that takes the value of 1 for districts in the lowest 25th percentile of the cross-sectional distribution of exposure pre-2000's and 0 otherwise, and another dummy variable that takes the value of 1 for districts in the top 25th percentile of the cross-sectional distribution of exposure pre-2000's and 0 otherwise. We proceed to re-estimate the baseline specification for this sub-samples of the panel of

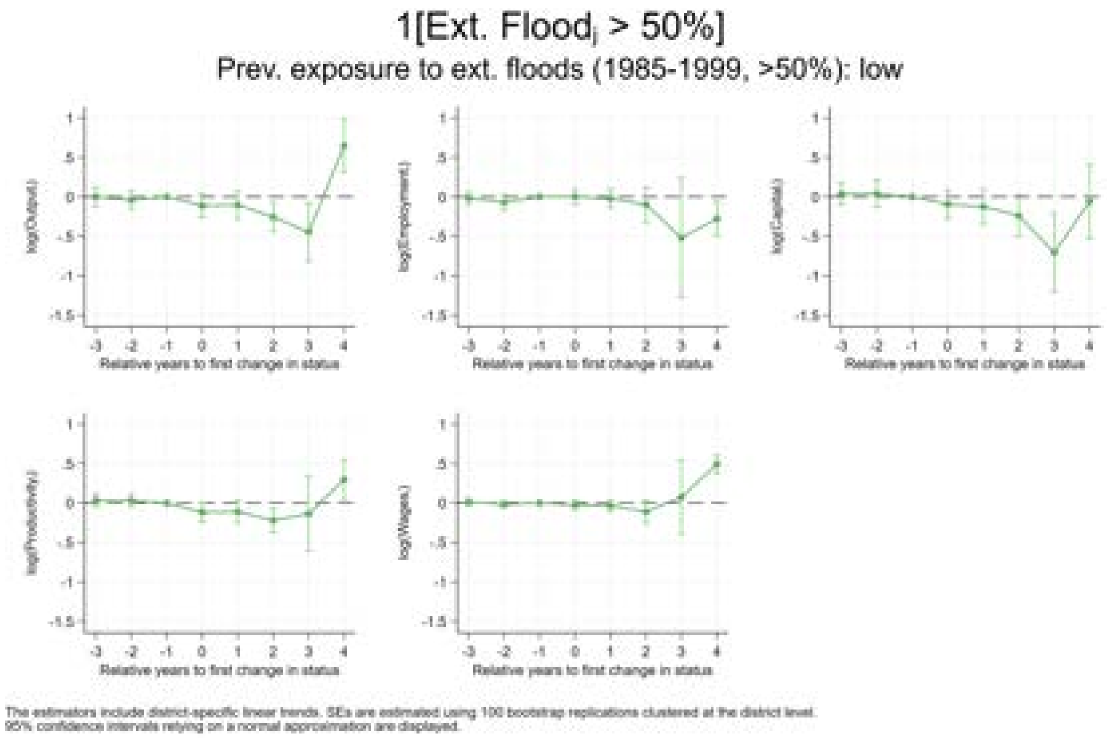

Figure 4: Effect of severe-extreme floods on establishment-level outcomes: Establishments in historically low-exposure locations

establishments, and report the results below.

Figure 4 reports the DID_l estimates for the sample in the bottom 25th percentile of previous exposure to severe-extreme floods. The pattern found in the previous sections remains robust: output, employment, capital accumulation, labor productivity and wages fall more for establishments that were exposed to severe-extreme floods than in establishments that were not. Once again, the effects build over time, and in the case of output, labor productivity and capital become statistically significant at the 5% level after two years. Importantly, the comparison group in this exercise is composed by establishments that have not-yet experienced a severe-extreme flood up to horizon l, but that are also located in districts in the bottom 25th percentile of previous exposure to severe-extreme floods. A surprising pattern that also emerges from this analysis is a "rebound" effect that takes place four years after the incidence of the first severe-extreme flood, that implies an increase, on average, of output and wages.

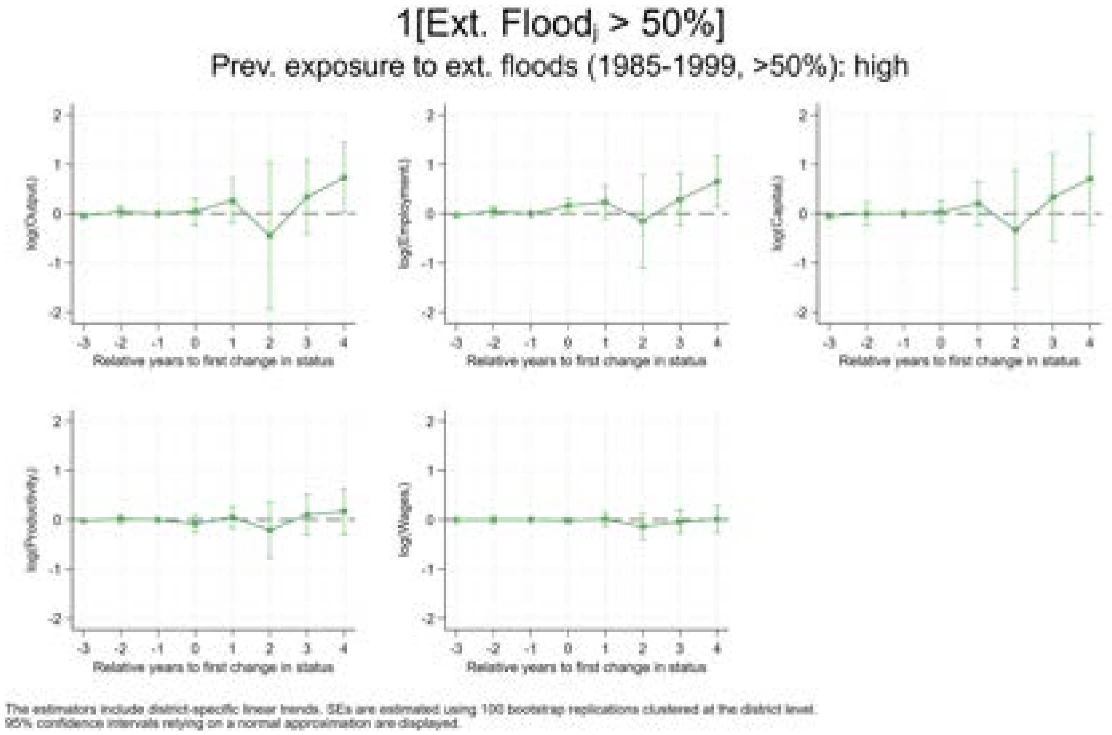

Figure 5: Effect of severe-extreme floods on establishment-level outcomes: Establishments in historically high-exposure locations

On the other end of the spectrum, Figure 5 reports the DID_l estimates for the sample in the top 25th percentile of previous exposure to severe-extreme floods. Here, the pattern found in the previous sections breaks: if anything, it seems like output, employment, and capital accumulation remain constant in the year of the first extreme-severe flooding event, and increase in the following years. Meanwhile labor productivity and wages remain unchanged during the whole event-study period. However, as it was the case in the bottom 25th percent, the effects for output, capital accumulation and labor build over time, especially after the second year, when it seems to recede: this could be the effect of additional severe-extreme floods that take place on average two years after the first event; we need to explore the path of flooding events for these sub sample in the data. In terms of statistical significance, DID_0^l is positive and statistically significant at the 5% level: in the year of the first extreme-severe flooding event, employment rises by a larger proportion for establishments that were exposed than in establishments that were not. As mentioned before, these effect build up across time, and are statistically significant after four years for output and employment. As it was the case for the bottom 25th percentile, the comparison group in this exercise is composed by establishments that have not-yet experience a severe-extreme flood up to horizon l, but that are also located in districts in the top 25th percentile of previous exposure to severe-extreme floods.

In conclusion, our analysis points towards existing heterogeneity in the effects of extreme-severe floods, dependent on the level of previous exposure to these types of events in the past: in districts in which extreme-severe flooding was not frequent during the 15 years prior to our sample, establishment-level outcomes seem to follow the same patterns as in previous sections, in which establishments exposed to extreme weather events did relatively worse to their counterparts not experiencing these events. On the other hand, establishments in districts in which extreme-severe flooding was more frequent during the 15 years prior to our sample period, establishments exposed to these extreme weather events, if anything, seem to do better than their non-exposed counterparts. The empirical evidence on this section seems to point towards an important role of adaptation.

3.3.4 Industry heterogeneity and linkages to other sectors

In this section, we explore yet another dimension of heterogeneity across establishment in our data: industry heterogeneity and link to other sectors. In general, it does not need to be the case that the effect of extreme weather events on establishment-level outcomes needs to be the same across different industries: there might be some activities that can be specifically more affected, due to the nature of the inputs they use for production, the outputs they produce, or the linkages to other sectors within or outside manufacturing. To further explore these potential differences across industries, in this section we re-estimate the baseline specification, allowing for the possibility of heterogeneous impacts depending on i) the establishment's industry and ii) how much that industry is linked to Agriculture, Construction and Inland Transport, which are sectors that we do not observe directly because the Annual Survey of Industries is limited to manufacturing. With this purpose, we use the 2000 Input-Output table from the Asian Development Bank to define 14 broad manufacturing industries and compute the direct supply and demand links with Agriculture and Construction for each of these groups. To do so, we compute the Leontief Inverse matrix from the Input-Output table, which captures both direct and indirect links across sectors. In this matrix L, a typical element $l_{i,j}$ captures the dollars of good j needed to produce one dollar of good i, both directly and indirectly through other sectors. [6]

[6] To compute the Leontief Inverse matrix, we first compute the Direct Requirement matrix (A), which can be easily obtained from the raw Input-Output data. This matrix captures only direct linkages, where a typical element $a_{i,j}$

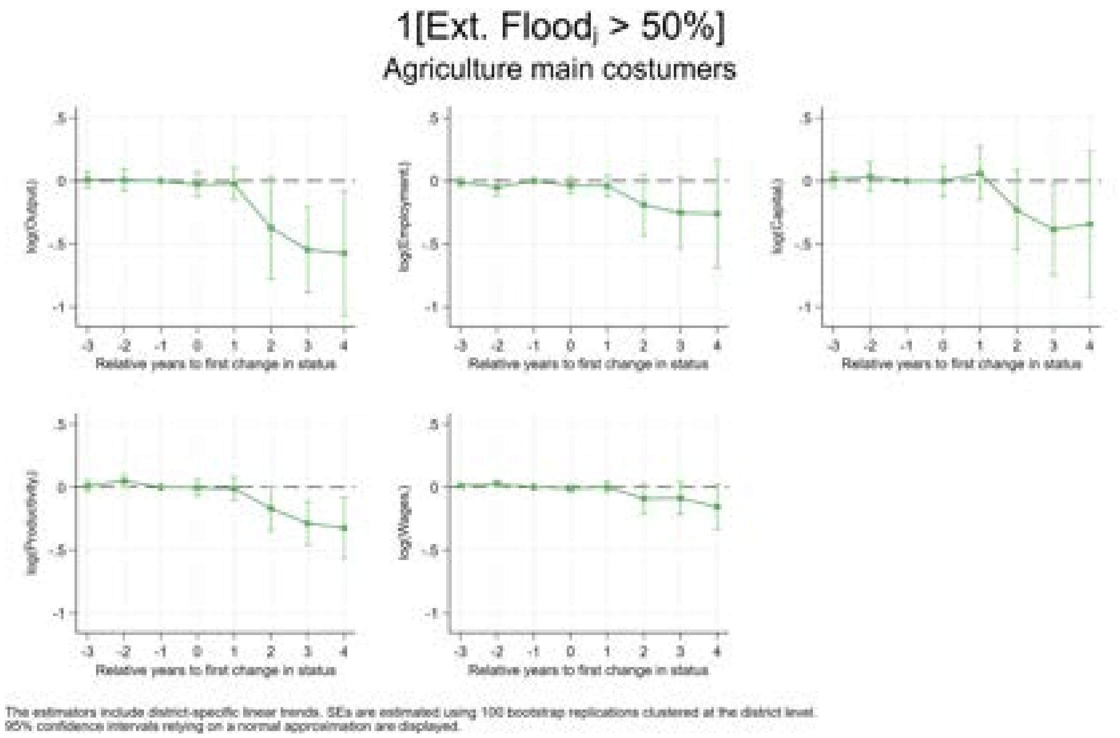

Figure 6: Effect of severe-extreme floods on establishment-level outcomes: Agriculture customers

With this sectoral data, we obtain the linkages of each of the 14 broad industries to Agriculture, Construction and Inland Transport, Section A.1 provides more details on the classification of these industries. Our goal is to explore whether the impact of our flood measure depends on the specific industry in which an establishment is classified into and/or how much that industry buys or sells to/from these sectors, as captured by the l_{ij} elements. To explore this potential heterogeneity, we re-estimate the baseline specification for three different sub-samples of our panel data: i) for industries catalogued as *Agriculture customers*, defined as the ones that spend 10 dollars or more in agricultural inputs per 100 dollars produced; ii) industries catalogued as *Transport suppliers*, defined as the ones from which the transport sector sources inputs, in a proportion of more than 5 dollars per 100 dollars produced, and iii) industries catalogued as *Construction suppliers*, defined as the ones from which the construction sector sources inputs, in a proportion of more than 5 dollars per

measures the dollars of good j needed to produce good i. Then, we follow Carvalho and Tahbaz-Salehi [2019] to compute the Leontief Inverse: $L = (I - A)^{-1}$. Figure 11 in the Appendix plots the non-diagonal elements of the Leontief Inverse

100 dollars produced.

Figure 6 reports the DID_l estimates for the sample of the *Agriculture customers*. The pattern found in the baseline specification shows up for this particular group: output, employment, capital accumulation, labor productivity and wages fall more for establishments that were exposed to severe-extreme floods than in establishments that were not. Importantly, the contemporaneous effect is statistically equal to zero in all cases, but it builds over time, and becomes statistically significant at the 5% level after three years. Importantly, the comparison group in this exercise is composed by establishments that have not-yet experienced a severe-extreme flood up to horizon l, but that are catalogued as *Agriculture customers*. These results point towards a critical response by establishments that source inputs from the agricultural sector, as they perform relatively poorly when hit by extreme weather events, and these effects seem to be dynamic, in that the build across time, and persistent.

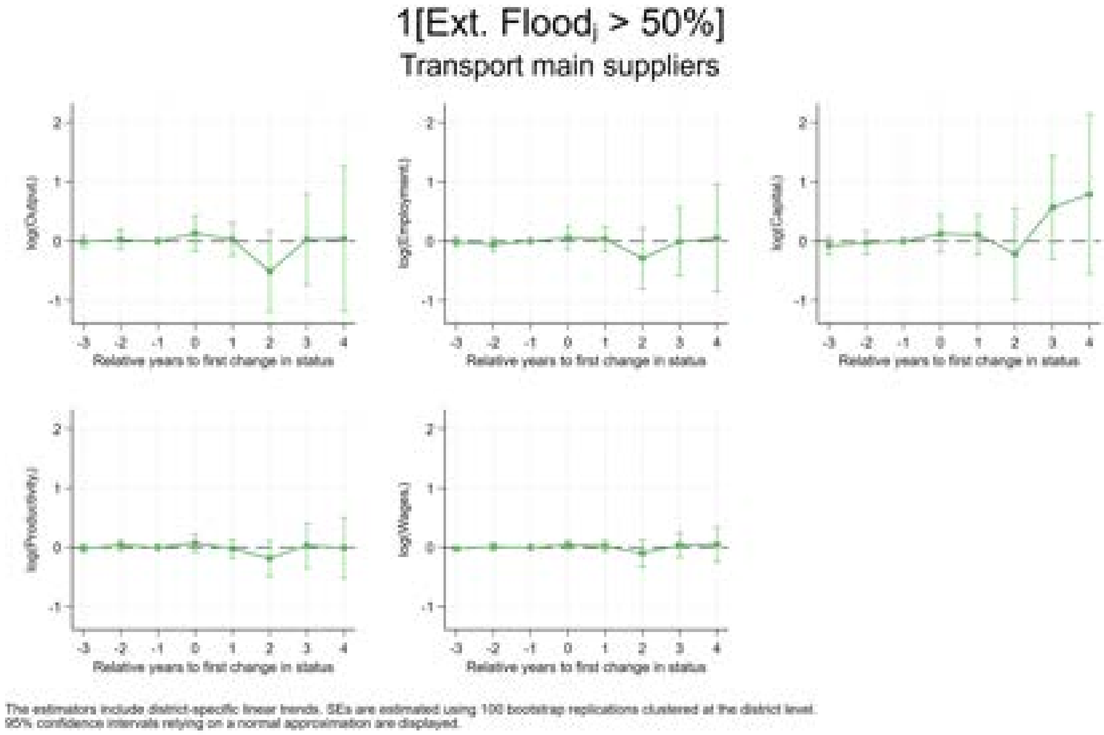

Figure 7: Effect of severe-extreme floods on establishment-level outcomes: Transport suppliers

Furthermore, we repeat the estimation exercise, this time for the sub-sample of *Transport suppliers* and *Construction suppliers*, and the results are reported in Figures 7 and 8, respectively. In this cases, as opposed to the results for *Agriculture customers*, the results are less clear: in all cases and for all horizons, the DID_l estimates are not statistically different from zero. Furthermore, there seems to be no particular differential response from establishments catalogued as *Transport suppliers* after an extreme-severe flood event, relative to establishments not exposed to these weather events, and, if anything, capital accumulation seems to increase three years after the initial change in treatment status. On the other hand, the responses of the *Construction suppliers* exhibits a similar pattern to the one in the baseline specification and for the *Agriculture customers*, but the confidence intervals for the estimates are relatively large, pointing to a large degree of uncertainty in the estimates.

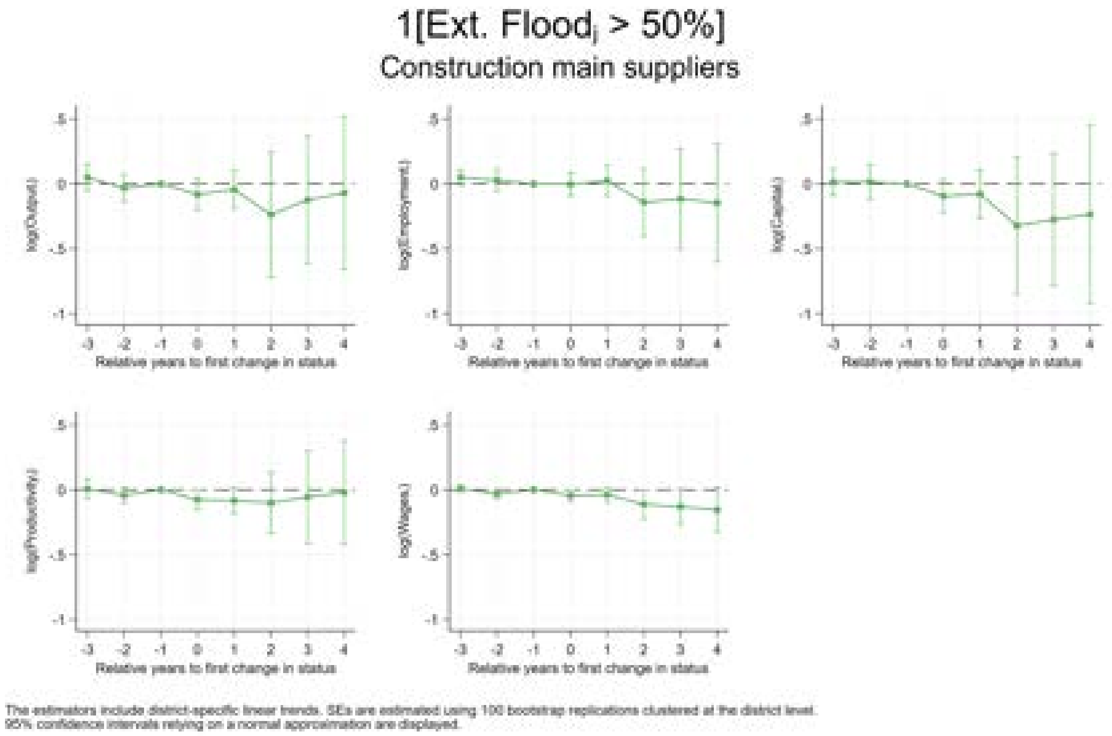

Figure 8: Effect of severe-extreme floods on establishment-level outcomes: Construction suppliers

In conclusion, the evidence from this section points towards an increased response of industries linked to the agricultural sector to extreme weather events, as firms catalogued as *Agriculture customers* that are exposed to extreme-severe floods during our sample period exhibit a worse performance in terms of total output, employment, capital accumulation, labor productivity and wages, relative to those establishments in the same sector but that are not exposed to these extreme weather events.

In order to better understand the mechanisms through which these heterogeneities, both in terms of industry and links to other sectors, play a role, we need to go to a more detailed level in the data and analyze the response of quantities produced and prices charged by establishments and the response of these variables to the exposure to extreme-severe floods, to be able to better assess the results presented so far.

4 Floods and Product Input-Output Linkages

4.1 Floods and Products: Direct Impact

The product dataset of the Annual Survey of Industries has been used by the literature to understand promotions of small scale industry Martin et al. [2017] and learning along the value chain Rachapalli [2021], among other topics. However, to the best of our knowledge, we are the first ones to document the impact of floods in the products of manufacturing establishments in India. In addition, we can both observe the price and quantity of both products produced and used as an input in our dataset. Finally, it is worth noting that the products are identified at a very detailed dimension in our data, with approximately 4,000 unique product codes.

For this section, we restrict our analysis to the 2001-2007 years following Rachapalli [2021], as the product codes are the most consistent within this period. To analyze the impact of our flood measure on the production of manufacturing establishments, we use the same empirical strategy outlined in section 3.2, following De Chaisemartin and d'Haultfoeuille [2022a]. Therefore, our treatment is defined as the first time a product in a given establishment is affected by an Extreme flood that affects more than 50% of the district area. In this case, the control group will be composed of establishments in districts that are never affected by floods in our sample period.

Figure 9 shows that output products of establishments affected by an extreme flood seem to have lower sale value but higher price, suggesting a supply shock to production. However, the results are not significant at the 95% level.

In order to better understand the mechanisms at work, we explore the differential impacts by industry type. One of the sectors that we analyze is "Agriculture Customers": manufacturing industries such as *Textiles* or *Wood* that use more than 10 dollars of inputs from Agriculture, for a 100 dollars

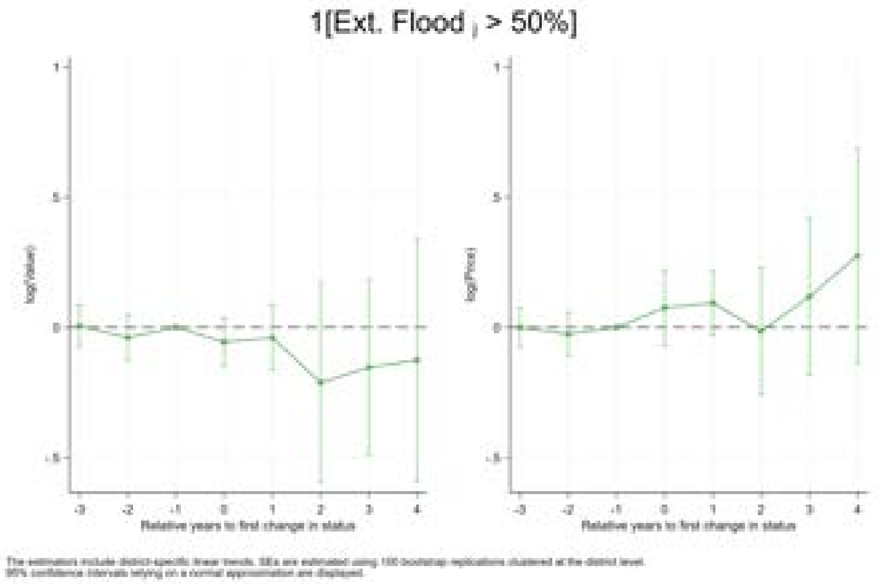

Figure 9: Flood Impact on Output Value and Price

produced.[7] Figure 10 shows the main results for these sectors, suggesting that the previous results are stronger for manufacturing industries that need inputs from the Agriculture sector. This finding relates to Brey and Hertweck [2019], who find that droughts in India are a source of inflationary dynamics in food prices. In our case, we focus on large flood, and we analyze manufacturing industries directly downstream of Agriculture, finding similar increases in prices, especially one year after the first extreme flood affects the establishment district.

The analysis of the direct impact of floods on products leaves some open questions that need further analysis. First, in Appendix Figure 14 we find that for the sector of *Other_Manufacturing*, output prices at the product level seem to decrease after a flood hits an establishment for the first time, suggesting a long run effect. In addition, when analyzing the value and price of inputs, Figure 15 in the Appendix shows that input prices fall after two periods. Further analysis needs to be done to fully understand the dynamics of value and prices in this context.

[7] See the Appendix for a full list of these sectors.

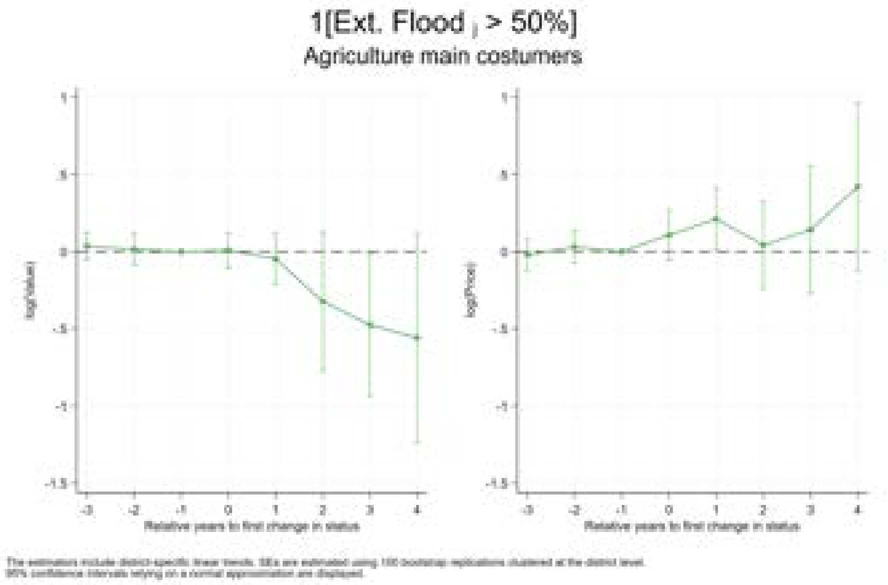

Figure 10: Flood Impact on Output Value and Price, Agriculture Customers

4.2 Indirect Flood Impact: Measuring Product Exposure

Apart from the direct flood impact, the richness in our data allows us to study the propagation or dampening of floods in India through Input-Output linkages. For the 2011 earthquake in Japan, Carvalho et al. [2021] show that natural disasters propagate through firm networks, as more than half of the aggregate GDP impact happened in regions that were not directly affected. An additional hypothesis is that Input-Output linkages absorb part of the impact of natural disasters. This mechanism is present in the analysis of the global car industry by Castro-Vincenzi [2022], while Albert et al. [2021] show that factor mobility across regions in Brazil can dampen the impact of droughts. In this section, our goal is to understand how Input-Output linkages in India propagate or dampen the impact of floods.

By focusing on production networks, our work would be closer to Carvalho et al. [2021], though the context and the data are different. In our case, floods are an extreme weather event that occurs recurrently in India, while the analyzed earthquake in Japan corresponds to a one-time shock. We believe that an additional reason to study floods is the fact that climate change will increase their frequency and severity, especially in developing economies. In terms of the data, the main limitation in the Annual Survey of Industries is that we do not observe the network of trade between establishments, unlike Carvalho et al. [2021] or Barrot and Sauvagnat [2016]. However, usually the network data measures transaction value, while we can differentiate between price and quantity of products and inputs, providing new facts to the literature.

With the purpose of illustrating the possible propagation of floods across space in India, we use two main product datasets available in the Annual Survey of Industries: output products sold (O) and input products used (I). We will combine the two datasets with the following two statistics: $Share^O$ and $Share^I$, capturing respectively the share of product producers and the share of product users in areas affected by a flood. We exclude the own establishment when combining the output share affected by floods ($Share^O$) with the output dataset, and when combining the share of product buyers with the input dataset. Table 2 shows how we construct these variables in the Annual Survey of Industries, using an example of a product from our data: "Wooden doors/windows".

Year	**Product**	**O or I**	**Location**	**Flood$_{>50\%}$**	**Value**	**Share^O**	**Share^I**
2002	"Wooden doors/windows"	O	1	**1**	1000	0%	20%
2002	"Wooden doors/windows"	O	2	0	500	80%	20%
2002	"Wooden doors/windows"	O	3	0	250	66.6%	20%
2002	"Wooden doors/windows"	I	4	**1**	500	57.1%	0%
2002	"Wooden doors/windows"	I	5	0	2000	57.1%	100%
2003	"Wooden doors/windows"	O	1	0	1000	66.6%	80%
2003	"Wooden doors/windows"	O	2	**1**	500	0%	80%
2003	"Wooden doors/windows"	O	3	0	250	33.3%	80%
2003	"Wooden doors/windows"	I	4	0	500	28.6%	100%
2003	"Wooden doors/windows"	I	5	**1**	2000	28.6%	0%

Table 2: Example of Product Exposure to Floods

We can focus first on the data for the year 2002: the first three rows describe three fictitious establishments that produce this product as an output (O) in three different locations, and with some value sold (1000, 500 and 250). For each of the three establishments, the variable $Share^O$ computes *how exposed to floods were potential competitors*. As an example, the establishment in location 2 faces competitors in locations 1 and 3, where 80% of the value produced by these competitors is in areas affected by a flood (1000/1250). Notice that we exclude the own production when looking at the variable $Share^O$ in combination with the product dataset. We repeat the same exercise, filling the first three rows of the column $Share^O$.

The fourth and fifth rows describe two establishments that use this product as an input (I). We are also interested in measuring the downstream propagation of floods: it might be that if many producers of "Wooden doors/windows" are affected by floods, also firms that need it as an input change their decisions. With this purpose, we compute the share of all output producers in affected areas, and combine it with our input data. Following the same example, in 2002 our $Share^O$ will be equal to 57.1% (1000/1750) for the fourth and fifth row. In this case, the variable $Share^O$ measures *how exposed to floods were potential suppliers.*

We can repeat the same procedure to measure the exposure of input users (I) of "Wooden doors/windows", where only one establishment is affected by a flood in 2002. In this case, we create the variable $Share^I$, that will take the value of 20% (500/2500), capturing the share of the total value of this product that is used as an input in areas affected by floods. When merging this variable with our output data, we will measure *how exposed to floods were potential customers.* Following a similar reasoning, we exclude the own establishment when combining the variable $Share^I$ with the input dataset, which yields 0 and 100% for establishments in locations 4 and 5. In this last case, we would measure *how exposed to floods were other product customers.* Finally, it is important to notice that the spatial distribution of floods will induce changes in the affected establishments, which will be captured by the changes in our variables $Share^O$ and $Share^I$ for 2003.

4.3 Propagation of Floods through Product Networks

We explain now how we build similar variables in the Annual Survey of Industries, and how we use them to study the propagation of floods across space. First, we will explain the specification that we run in our data on output products of establishments, and later we will discuss the analysis on manufacturing inputs.

Flood Propagation in Output Data

$$y^O_{k,i,j,t} = c + \gamma Share^I_{-i,k,t} + \theta Share^O_{k,t} + \sigma_{s,t} + \delta_j + \alpha_i + \rho_k + \epsilon_{k,i,j,t}$$

The dependent variable $y^O_{k,i,j,t}$ captures the log of an output outcomes at the product level of product k, produced by establishment i in district j at year t. The four output outcomes analyzed are value sold v^O, quantity manufactured q^O_m, quantity sold q^O_s and price p. In terms of the independent variables, we measure the following two dimensions of flood propagation.

1. *How exposed to floods were potential competitors:*

$$Share^{O}_{-i,k,t} \equiv 100 * \frac{\sum_{-i} 1(\textit{Severe/Extreme Flood affecting } j > 50\%) \cdot v^{OUT}_{kijt}}{\sum_i v^{OUT}_{kijt}}$$

2. *How exposed to floods were potential customers*

$$Share^{I}_{kt} \equiv 100 * \frac{\sum_{i} 1(\textit{Severe/Extreme Flood affecting } j > 50\%) \cdot v^{IN}_{kijt}}{\sum_i v^{IN}_{kijt}}$$

We define v^{OUT}_{kijt} as the value of product k when produced by firm i, in district j, at time t; and v^{IN}_{kijt} is the value of product k when used as an input by firm i, in district j, at time t. The two independent variables $Share^{O}_{-i,k,t}$ and $Share^{I}_{kt}$ mimic the first three rows in Table 2, where $1(\textit{Severe/Extreme Flood affecting } j > 50\%)$ is an indicator function that takes the value of 1 if an establishment is in a location affected by a flood. We also include sector-year ($\sigma_{s,t}$), district (δ_j), establishment (α_i) and product levels (ρ_k).

With the purpose of only capturing the propagation effect of floods through product markets, we exclude all producer establishment in districts that have been affected by floods in a given year. In the example of Table 2, we would be interested in the outcome of the establishment in location 2, across the years 2002 and 2003. Even though this establishment has not been affected by floods in these two years, the share of output and input flooded introduce variation in the exposure of that product to floods across years. We estimate the following regression through OLS, relying on the exogeneity assumption that the exact timing and location of extreme floods is exogenous. Columns (1-4) of Table 3 show the results of this regression for the different outcomes of products produced.

Flood Propagation in Input Data

We consider a similar analysis for our input data, where $y^{I}_{k,i,j,t}$ captures an input measure of establishment i in district j, purchasing input k in year t. We include three variables as possible outcomes: log of value purchased v^I, quantity q^I and price p^I.

$$y^{I}_{k,i,j,t} = c + \gamma Share^{I}_{-i,k,t} + \theta Share^{O}_{k,t} + \sigma_{s,t} + \delta_j + \alpha_i + \rho_k + \epsilon_{k,i,j,t}$$

In addition, we consider the following two mechanisms in our input dataset:

1. *how exposed to floods were potential suppliers*:

$$Share^{O}_{ikt} \equiv 100 * \frac{\sum_{-i} 1(Severe/Extreme\ Flood\ affecting\ j > 50\%) \cdot v^{OUT}_{kijt}}{\sum_{i} v^{OUT}_{kijt}}$$

2. *how exposed to floods were other product customers*

$$Share^{I}_{-i,k,t} \equiv 100 * \frac{\sum_{i} 1(Severe/Extreme\ Flood\ affecting\ j > 50\%) \cdot v^{IN}_{kijt}}{\sum_{i} v^{IN}_{kijt}}$$

The value of inputs is defined in a similar way to the value of products produced, we use the same set of fixed effects, and we rely on the same exogeneity assumptions. To compare with the example with the "Wooden doors/windows", the independent variables are analogous to rows four and five of Table 2. In addition, we exclude the set of establishments that buy inputs and are located in districts affected by floods. The results of the regression on input variables are shown in columns (5-7) of Table 3. For the 8 years analyzed, we find that there is only propagation of floods in the first regressions with output data, but not in the input dataset. If the share of competitors' value produced in flooded areas ($Share^{O}_{-i,k,t}$) increases by 10 percentage points, the quantity manufactured by other establishments decreases by 2%, the quantity sold by 1% and the price increases by 1%. Then, when the locations of competitors are flooded, establishments experience an increase in the price and a decrease in the quantity of outputs produced, even if they are not affected by floods themselves. This suggests that floods induce a supply shock that propagates to other regions, reducing quantity produced and increasing the price at which products are sold.

Additionally, we find some evidence of other propagation mechanism. In particular, an increase in 10 percentage points in the share of potential customers in flooded areas ($Share^{I}_{kt}$) decreases the price of products produced by 1%. Even though the quantity produced does not change as a consequence, this result suggests that the demand for products decreases when many users of a given good are located in flooded areas.

These results are significant at the 95% confidence level, and suggest that the effects of floods in India are not limited to the area affected directly. While Carvalho et al. [2021] had already documented the propagation of natural disasters through production networks, we provide empirical evidence in a different setting: a developing economy facing a recurrent extreme weather event. In addition, we

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	v	q_m	q_s	p	v	q	p
Share^{O}_{-ikt}	-0.000	-0.002***	-0.001**	0.001**			
	(0.00)	(0.00)	(0.00)	(0.00)			
Share^{I}_{kt}	-0.000	0.000	0.001	-0.001**			
	(0.00)	(0.00)	(0.00)	(0.00)			
Share^{O}_{kt}					-0.000	-0.000	0.000
					(0.00)	(0.00)	(0.00)
Share^{I}_{-ikt}					-0.000	-0.000	-0.000
					(0.00)	(0.00)	(0.00)
R^2	0.804	0.850	0.838	0.836	0.774	0.763	0.787
Observations	283980	283980	283980	283980	558693	558693	558693
Districts	476	476	476	476	483	483	483
Industry × Year FE	✓	✓	✓	✓	✓	✓	✓
District FE	✓	✓	✓	✓	✓	✓	✓
Establishment FE	✓	✓	✓	✓	✓	✓	✓
Product FE	✓	✓	✓	✓	✓	✓	✓
Estimate	OLS	OLS	OLS	OLS	OLS	OLS	OLS

Standard errors in parenthesis. Errors clustered at the district level, sample weights used in regression

Share^{O}_{kt}: Output value share by flooded firms. Share^{O}_{-ikt}: Output value share by flooded firms excluding producer i (0-100).

Share^{I}_{kt}: Input value share by flooded firms (0-100). Share^{I}_{-ikt}: Input value share by flooded firms excluding buyer i (0-100).

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Impact of Flood on Other Establishment Output (1-4) and Input (5-7)

show that the results affect both price and quantity in unaffected areas.

5 Conclusion

As climate change increases the intensity and frequency of floods, there is a pressing interest to understand their economic impact in developing economies. In this paper, we analyze the impact of the 15 most extreme floods in the manufacturing sector in India from 2000 to 2007, using the empirical strategy proposed by De Chaisemartin and d'Haultfoeuille [2022a]. We find that capital and output fall, especially in areas that have experienced less floods in the previous 15 years. In addition, we explore possible heterogeneties depending on the Input-Output linkages of the manufacturing industries to non-manufacturing sectors. The damaging impacts of floods in India during this period is stronger for industries that rely on Agricultural inputs.

The richness of the data from the Annual Survey of Industries allows us to study the impact at the product level. Extreme floods seem to decrease the value sold and increase the output price, especially for industries that need Agricultural inputs. In addition, we explore an interesting margin of our dataset: the fact that the same product is produced and used as an input in some areas exposed to floods, where the level of exposition changes across years. This allows us to consider the propagation of floods through Input-Output linkages, by analyzing the impact of product exposure on establishments located in areas not affected by floods. We find that when a product is produced mostly in areas affected by a flood, establishments in unaffected areas also sell and buy the same product at a higher price and by a lower quantity. When potential customers are located mostly in affected areas, we observe that the output price decreases.

References

C. Albert, P. Bustos, and J. Ponticelli. The effects of climate change on labor and capital reallocation. Technical report, National Bureau of Economic Research, 2021.

C. A. Balboni. *In harm's way? Infrastructure investments and the persistence of coastal cities.* PhD thesis, MIT, 2021.

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

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

B. Brey and M. S. Hertweck. Agricultural productivity shocks and poverty in india: The short-and long-term effects of monsoon rainfall. 2019.

V. M. Carvalho and A. Tahbaz-Salehi. Production networks: A primer. *Annual Review of Economics*, 11:635–663, 2019.

V. M. Carvalho, M. Nirei, Y. U. Saito, and A. Tahbaz-Salehi. Supply chain disruptions: Evidence from the great east japan earthquake. *The Quarterly Journal of Economics*, 136(2):1255–1321, 2021.

J. Castro-Vincenzi. *Climate Hazards and Resilience in the Global Car Industry.* PhD thesis, Princeton, 2022.

C. De Chaisemartin and X. d'Haultfoeuille. Difference-in-differences estimators of intertemporal treatment effects. Technical report, National Bureau of Economic Research, 2022a.

C. De Chaisemartin and X. d'Haultfoeuille. Two-way fixed effects and differences-in-differences with heterogeneous treatment effects: A survey. Technical report, National Bureau of Economic Research, 2022b.

K. Desmet, R. E. Kopp, S. A. Kulp, D. K. Nagy, M. Oppenheimer, E. Rossi-Hansberg, and B. H. Strauss. Evaluating the economic cost of coastal flooding. *American Economic Journal: Macroeconomics*, 13(2):444–86, April 2021. doi: 10.1257/mac.20180366. URL `https://www.aeaweb.org/articles?id=10.1257/mac.20180366`.

J. Gallagher. Learning about an infrequent event: evidence from flood insurance take-up in the united states. *American Economic Journal: Applied Economics*, pages 206–233, 2014.

S. Gandhi, M. E. Kahn, R. Kochhar, S. Lall, and V. Tandel. Adapting to flood risk: Evidence from a panel of global cities. Technical report, National Bureau of Economic Research, 2022.

F. Hossain. Creative destruction or just destruction? effects of floods on manufacturing establishments in india. *Working Paper*, 2020.

S. Jayachandran. Selling labor low: Wage responses to productivity shocks in developing countries. *Journal of political Economy*, 114(3):538–575, 2006.

R. Jia, X. Ma, and V. W. Xie. Expecting floods: Firm entry, employment, and aggregate implications. 2022.

A. Kocornik-Mina, T. K. McDermott, G. Michaels, and F. Rauch. Flooded cities. *American Economic Journal: Applied Economics*, 12(2):35–66, 2020.

L. A. Martin, S. Nataraj, and A. E. Harrison. In with the big, out with the small: Removing small-scale reservations in india. *American Economic Review*, 107(2):354–86, 2017.

X. Pang and P. Sun. *Moving into Riskyy Floodplains: the Spatial Implication of Flood Relief Policies.* PhD thesis, Pennsilvania State University, 2022.

N. Pankratz and C. Schiller. Climate change and adaptation in global supply-chain networks. In *Proceedings of Paris December 2019 Finance Meeting EUROFIDAI-ESSEC, European Corporate Governance Institute–Finance Working Paper*, number 775, 2021.

M. Pelli, J. Tschopp, N. Bezmaternykh, and K. Eklou. In the eye of the storm: Firms and capital destruction in india. *Available at SSRN 3449708*, 2022.

H.-O. Pörtner, D. C. Roberts, H. Adams, C. Adler, P. Aldunce, E. Ali, R. A. Begum, R. Betts, R. B. Kerr, R. Biesbroek, et al. Climate change 2022: Impacts, adaptation and vulnerability. *IPCC Sixth Assessment Report*, pages 37–118, 2022.

S. Rachapalli. Learning between buyers and sellers along the global value chain. Technical report, Working Paper, 2021.

S. Rao, S. Koirala, C. Thapa, and S. Neupane. When rain matters! investments and value relevance. *Journal of Corporate Finance*, 73:101827, 2022.

E. Somanathan, R. Somanathan, A. Sudarshan, and M. Tewari. The impact of temperature on productivity and labor supply: Evidence from indian manufacturing. *Journal of Political Economy*, 129(6):1797–1827, 2021.

A Industry Linkages with Manufacturing

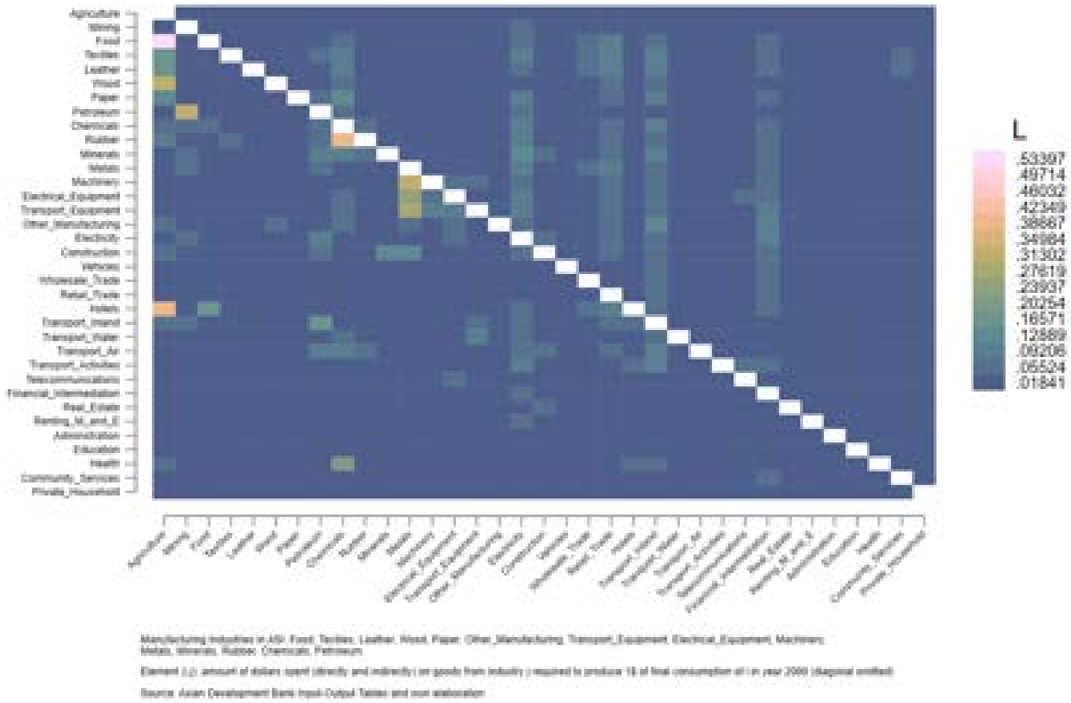

Figure 11: Direct and Indirect Links across 35 India sectors in 2000 (Leontief Inverse Matrix)

A.1 Manufacturing Industries by Type:

We list below the four classifications of industries, depending on their Input-Output linkages with three key sectors outside of manufacturing: Agriculture, Transport and Construction. As it can be seen in Figures 12 and 13, manufacturing industries rely more on Agriculture as customers than as suppliers. With respect to Transport and Construction, we found substantial heterogeneity in the industries supplying them, while all manufacturing purchased from them in a similar fraction. For these reasons we created the three industry groups: *Agriculture Customers*, *Transport Suppliers* and *Construction Suppliers*. The manufacturing industries without strong connections to any of these are grouped into *Other Manufacturing*.

1. Agriculture Customers (>10 dollars spent in Agriculture per 100 dollars produced); *Leather*, *Wood*, *Food*, *Paper* and *Textiles*.

2. Transport Suppliers (>5 Transport dollars spent in industry per 100 Transport dollars produced): *Petroleum*, *Transport Equipment*

3. Construction Suppliers(>5 Construction dollars spent in industry per 100 Construction dollars produced): *Minerals*, *Metals*

4. Other Manufacturing: *Chemicals*, *Electrical Equipment*, *Machinery*, *Other Manufacturing* and *Rubber*

These industries can be merged by NIC-98 to the Annual Survey of Industries.

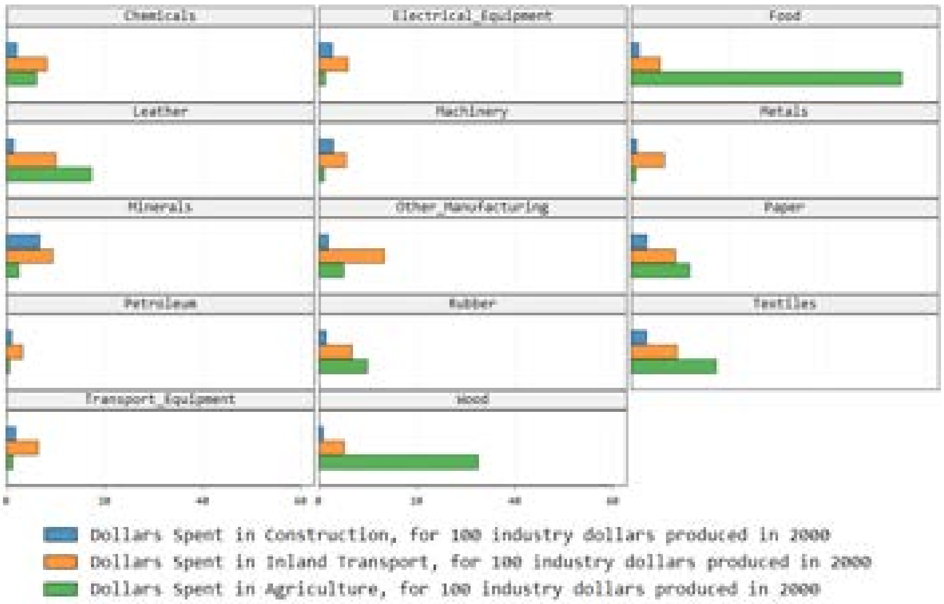

Figure 12: Suppliers of Manufacturing Sectors

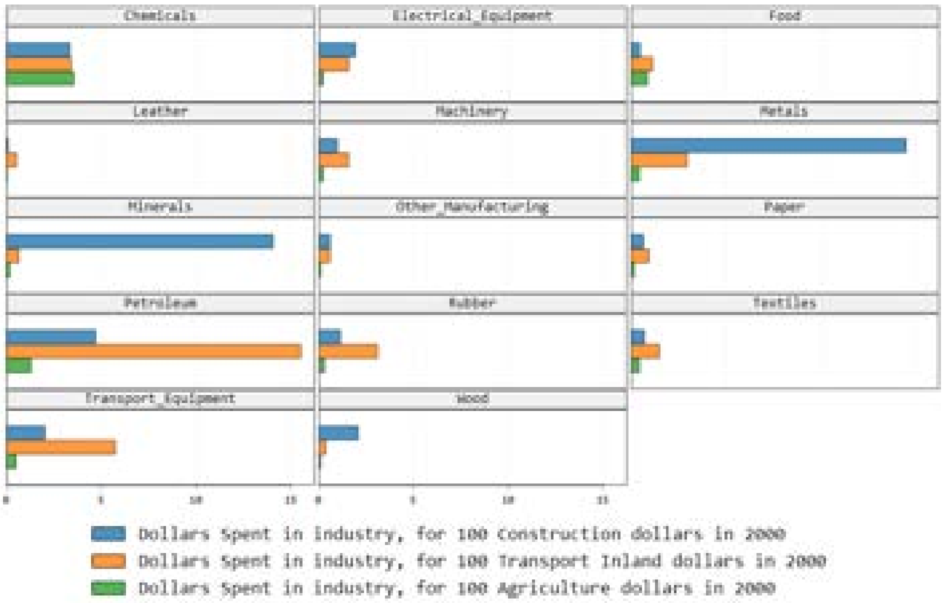

Figure 13: Customers of Manufacturing Sectors

B Additional Results at the Product Level

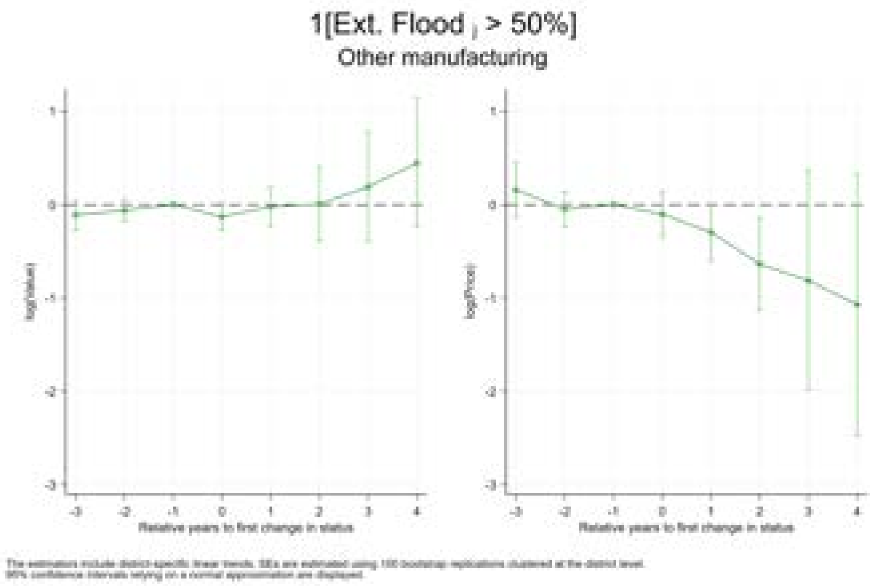

Figure 14: Flood Impact on Output Value and Price, Other Manufacturing

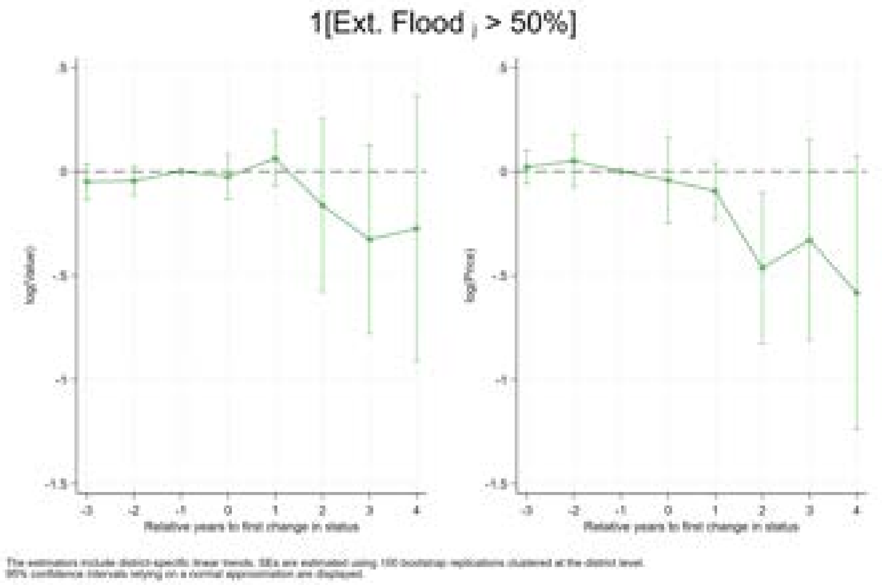

Figure 15: Flood Impact on Input Value and Price

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April 4, 2023

To whom it may concern,

I hereby confirm that Alejandro Rábano is currently registered as a full time student in the PhD in Economics, Finance and Management at Universitat Pompeu Fabra.

The academic length of the Programme is 3 academic years with 1 year extension if needed.

Mr. Rábano is expected to finish no later than September, 2025.

Sincerely yours,

Davide Debortoli

Director PhD in Economics, Finance and Management