Using Satellite-observed Geospatial Inundation Data to Identify the Impacts of Flood on Firm-level Performances: The Case of China during 2000–2009

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Abstract

Among the first in the literature, this paper combines high-resolution satellite-observed inundation maps with geocoded firm-level data to identify the flood exposure at the firm level. We apply the methodology to study the impact of floods on micro-level firm performances in China for the period 2000–2009. Being hit by a flood is associated with an annual loss of output and productivity of around 6% and 5%, respectively, which persists in the long run. The effects are heterogeneous across types of firms and locations of the floods. Firms that are tangible-asset intensive are more negatively affected by the flood events. Meanwhile, the effects on firms located in flood-prone counties are less severe and shorter-lived, suggesting better adaptation of firms experienced with floods. The impacts of floods extend to non-inundated firms in surrounding areas (of 4 kilometres in radius), but the negative effects are much smaller (2% on average) and diminish after three years. Firms beyond the immediate neighborhood expand their output from the second year onward, in contrast with the permanent shrinkage of the inundated firms. By aggregating the firm-level data to the county level, we further identify negative effects of floods at the extensive margin: the firm exit (entry) rate is higher (lower) in counties that are hit by floods, and the effects are stronger in counties subject to more severe floods.

Key Words: Floods; Natural Disasters; Firm Performance; China
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1 Introduction

The direct physical damage caused by a natural disaster can be learned soon after the occurrence of the event, but the indirect effects following the immediate impacts—including the time and resources to rebuild the productive capacities (capital stock, labor force and productivity)—are difficult to evaluate and measure. In this paper, we conduct one of the first studies to combine high-resolution satellite-observed inundation maps with geocoded firm-level data to identify the flood exposure at the firm level, and provide evidence on how exposure to flood events affects corporate performances in China for the period 2000–2009.

Floods are the most destructive and costly natural disaster in China, in terms of the frequency of occurrence and the extent of damages. Figure 1 presents the summary statistics of natural disasters that took place during the recent half century (1970–2021) in mainland China, based on the Emergency Events Database (EM-DAT) of the Centre for Research on the Epidemiology of Disasters (CRED).[1] Among all 900 hazard events that occurred during 1970–2021 in China, floods accounted for approximately one third in terms of frequency and one half in terms of total estimated damages in dollar value (adjusted for inflation). Each of these flood events on average caused 240 deaths, 8.4 million people affected (injured or homeless) and 2 billion US dollars of damages. These magnitudes are considerably higher than the global average (which are correspondingly 86 deaths, 0.8 million people affected, and 0.76 billion USD of damages). In addition, the frequency of floods in China has witnessed a nearly 10 times growth in the recent five decades, from 10 flood events during 1972–1981 to 98 during 2012–2021.[2] This is consistent with the report by the Intergovernmental Panel on Climate Change (Chaturvedi, Cheong, Luo, Singh and Shaw, 2022) that rising temperature increases the likelihood of natural hazards. Despite flood's catastrophic impacts and the prospect of its intensifying frequency in the future due to climate change in China, there have been few studies that systematically evaluate the effects of floods on corporate performances. How are the inundated firms affected in the aftermath of a flood event in terms of firms' input, output and productivity? How long does it take for these firms to restore normality? Which kind of firms are more vulnerable to floods and what are the factors that determine this vulnerability? Are there spillover effects on non-inundated firms in the neighboring areas? In this paper, we attempt to investigate these issues and identify the effects of flood on the firm performance measures, by the time horizon in the aftermath of the flood event,

[1] From among the "Natural" disaster group defined in EM-DAT, we exclude 13 disaster events that occurred during the period 1970–2021 in mainland China. These belong to "Biological" and "Extra-terrestrial" subgroups, which are not directly related to climate change.

[2] According to EM-DAT, the number of flood events in each of the five recent decades during 1972–2021 in mainland China are 10, 35, 58, 91 and 98, respectively.

by the distance to the inundation area, and by firm characteristics that might moderate firms' responses and vulnerability to flood hazards.

One of the main challenges in estimating the causal impact of floods on micro-level firm performances is identifying the set of inundated firms in each flood event. It requires precise information on the geographical location of the inundation area of each flood event and the operating location of each firm. The actual inundation maps and the geocoded firm locations are, however, not readily available. The influence scope of a flood event reported by governments or news media is typically at the administrative level (in the case of China, at the county level at the finest). This as we will document in the text is a poor proxy of the actual inundation area. Guiteras, Jina and Mobarak (2015) suggest that self-reported exposure is also not a reliable measure of true flood exposure. As such, we derive the data on the geospatial flood inundation areas from the Global Flood Database (GFD) developed by Tellman, Sullivan, Kuhn, Kettner, Doyle, Brakenridge, Erickson and Slayback (2021). In particular, the authors filtered high-frequency satellite imagery repositories and applied water detection algorithms to identify the precise inundation area. The database provides raster GeoTIFF images with a pixel resolution of 250 meters. For each raster, we use GIS software to extract the information we need and transform the raster to a polygon shapefile. This is done for each flood event taking place in China during the period studied. We then geocode the location data of all the firms operating across China during the same period. By combining these two sets of geographical data, we can identify the set of inundated firms in each flood event, and compute the distances of all non-inundated firms to the inundation areas (the latter to be useful in the analysis of spatial spillover effects). To the best of our knowledge, this is one of the first such studies in the literature to identify the flood exposure at the firm level, relying on satellite imagery data. We document in further details the data we use in Section 2.

Being hit by a flood may cause immediate as well as long-lasting damages to a firm's production activities, depending on how severe the flood event is and how long it takes to rebuild the production capacities and infrastructures. Firms located nearby but not directly exposed to a flood event may also be negatively affected if the transportation network in the area cannot be easily reorganized to eschew the nodes in inundated areas. Alternatively, non-inundated firms might benefit instead if market shares previously served by inundated firms are reallocated toward these firms. We employ an integrated econometric strategy to accommodate these potential dynamic and spillover effects, while controlling for many potential confounders.

We find that for the period studied, floods in China have reduced firms' production capacity (in terms of outputs and employment) and productivity both in the short and the long run, although capital stock can be recovered in the third year after the flood. The annual losses in output and productivity are as large as 6% and 5% (on average across horizons after the flood), respectively. Using concentric ring analysis, we observe significant and differential spillover effects for the non-inundated firms in the neighborhoods. Non-inundated Firms located within 4 kilometres from the inundated area are also negatively affected in their outputs, although the effects are much smaller (at 2% on average) and the firms could recover normality after three years. In contrast, firms that are located further away (between 6 and 18 kilometres from the inundated area) expand in their productions (in the second year onwards). The latter positive spillover effects suggest that production activities are reallocated geographically toward surrounding neighborhoods, consistent with the negative and permanent effects identified above for the inundated firms and areas.

We further investigate factors that could moderate firms' responses and vulnerability to flood hazards, including: firms' asset tangibility, ownership structure, trade status, and sector of production, as well as the characteristics of the county where firms are located. In addition to the effects at the intensive margin addressed above, we also examine the effects of flood hazards on firm entry and exit at the county level, hence providing evidence of potential negative effects of floods at the extensive margin. The estimation results are documented in Section 3. In Section 4, we address potential threats to identification (e.g., firms' endogenous relocation choice and past experiences with flood) and verify the robustness of the baseline results to these concerns. Below we survey the related literatures and highlight our contributions to these literatures.

1.1 Related Literatures

This paper is related to a number of studies that investigate the effects of natural disasters on micro-level entities. In most these studies, while the research subjects are individual households/workers (e.g., Anttila-Hughes and Hsiang, 2013; Yang and Choi, 2007; Auffhammer and Aroonruengsawat, 2011; Somanathan, Somanathan, Sudarshan and Tewari, 2021), plants/firms (e.g., Cachon, Gallino and Olivares, 2012; Graff Zivin and Neidell, 2014; Addoum, Ng and Ortiz-Bobea, 2020; Chen and Yang, 2019; Hossain, 2020), or products (e.g., Jones and Olken, 2010), the treatment groups are usually defined at the administrative geographical unit level, such as counties, provinces, districts or states. This is because the spatial resolution of economic data and that of weather/disaster data are usually not aligned. Either the individual entities' locations cannot be geocoded, so that the weather/disaster data has to be aggregated to an economically meaningful level that can be matched with the individual entity data for analysis;[3] or the geospatial data about the actual weather/disaster extents are not readily available, so that scholars can only use the affected administrative geographical areas as proxies for the actual influence scope, as commonly seen in news reports for floods, typhoons or earthquakes. Consequently, in both cases, the matching of the weather/disaster data and the economic data and the subsequent allocation of treatment status to individual entities would suffer measurement error problem (Hsiang, 2016).

The latter issue for floods, the disaster type of our interest in this paper, is specifically problematic when one administrative geographical location is reported as being flooded but in fact only a small part of that location is inundated. If one uses the reported administrative location as the measure for inundation extent and then matches it with geocoded firm data to allocate the treatment status of a firm, all firms located in the administrative location but out of the small true inundation area would be misclassified as inundated. If the number of misclassified firms makes up a large proportion, the estimation results should be severely biased. We will see later in the data section that this is the case if one uses the flood-affected regions or GIS polygons provided in the Emergency Events Database (EM-DAT) or the Dartmouth Flood Observatory (DFO) as the measure for inundation areas. Bearing this in mind, a key innovation of our study is the construction of a novel dataset that merges high-resolution satellite-observed flood extent data with comprehensive geocoded firm-level data. With the high spatial resolution of both disaster and economic data, the classification of treatment status is no longer restricted to administrative geographical areas but defined by the close vicinity of the event, remedying the measurement error problem.

Leiter, Oberhofer and Raschky (2009) and Noth and Rehbein (2019) are two of the few studies that evaluate the impacts of large-scale flood events on microlevel firm outcomes. Leiter, Oberhofer and Raschky (2009) study the effects of a major flood that occurred in 2000 in Europe on firms' capital, employment and productivity, by using a difference-in-difference (DID) approach. They emphasize the heterogeneous flood impacts on firms with different asset structures: in particular, companies with larger shares of intangible assets, e.g. patents and licenses, are less affected by flood hazard. Noth and Rehbein (2019) also use the DID approach to examine the effects of the 2013 Elbe flood on German firms' turnover, tangible fixed assets, leverage ratio and cash holdings. We deviate from these studies in two key aspects. First, both of these studies look at a single (year's) major flood event(s)

[3] Almost all the literature listed above are of this type. This is very common for studies on temperature and precipitation. For example, Somanathan, Somanathan, Sudarshan and Tewari (2021) studies the impact of temperature on labor in India. The firm data they use only documents the district each firm located and does not contain geographical coordinate information, hence they aggregate the temperature and rainfall data to district level and assign the weather data to the firms and workers according to the district in which they are situated. See Dell, Jones and Olken (2014) for a discussion about the aggregation of weather data and a comprehensive review of climate-economy literature.

and use the DID method, dividing the study periods (6 years in both papers) into the pre- and post-flood periods and comparing firms' performances across the periods, to estimate the treatment effects. In contrast, we build a detailed panel of geo-referenced data on flood extents and on firms at annual frequency from 2000 to 2009. This allows us to provide a comprehensive impact evaluation of flood hazards on Chinese firm-level performances across years and locations. Second and more importantly, as highlighted above, instead of using large administrative geographical regions to define a firm's treatment status, we use high resolution satellite-observed flood extent data, associated with geocoded firm data, to identify whether a firm is inundated or not. This classification greatly improves the measurement precision of the treatment status upon those in the flood literature.

Another closely related work is Hossain (2020), who also uses the remote sensing data from satellites to produce the inundation maps, and then combines them with the establishment-level data from formal and informal sectors to study the impact of floods on manufacturing establishments and labor in India. The treatment group in that work, however, is district rather than establishment. The key independent variable is not the exposure of each individual establishment but the flood intensity of the district which the establishment is located in. The reason is that the establishments are only identifiable at the district level. Hu, Pant, Hall, Surminski and Huang (2019) also construct panel data of inundation areas and geocoded firms to investigate the flood's impacts on individual companies in China over the period 2003–2010. In addition to estimation strategies, we improve upon their data in two aspects. First, the DFO database they use are subject to the critique discussed above: it provides GIS polygons for the geographic areas affected by flood events, which are determined based on media news or government sources and are typically much larger than the actual areas of inundation. Second, we use the Annual Surveys of Industrial Firms (ASIF) conducted by China, which covers all industrial firms with sales above 5 million RMB and is more comprehensive than the Orbis dataset used in their study.

We compare the dynamic effects of floods with recent studies under a unified framework. Kocornik-Mina, McDermott, Michaels and Rauch (2020) studies how large urban floods affect the economic activities across and within cities in a global scope. They find that a flooded city's economic activity, as measured by the intensity of night lights, declines by 2 to 8 percent in the year of the flood but typically fully recovers immediately within the year of the flood event. Gandhi, Kahn, Kochhar, Lall and Tandel (2022) also uses night lights data as proxy for economic activity to study the impact of floods on cities around the world, but in a monthly frequency instead of yearly as in Kocornik-Mina, McDermott, Michaels and Rauch (2020). They further assert that the economic activity in flooded cities is restored to pre-disaster level in 1 to 2 months after the flooding, depending on the income status of the country where the city is in. In our paper, in contrast, we find that the aggregate economic effects in city-level mask the considerably differential effects of flooding on inundated and non-inundated firms within the city, and floods have far longer-term or even permanent adverse impact on the flooded firms.

Gandhi, Kahn, Kochhar, Lall and Tandel (2022) also documents that cities that are more vulnerable (measured by the frequency of severe flood events occurred in the city) to floods experience lower population growth. However, these cities suffer less, almost half, from flooding than cities that do not face recurrent floods. We find similar patterns for individual firms: by aggregating firm data into county level according to their locations, the exit (entry) rate is significantly higher (lower) for counties that are hit by floods, and the deterring effect is severer in counties with more firms being inundated. On the other hand, the damaging effect on firms that are located in flood-prone counties is considerably smaller than the effect on firms that suffered inundation in only one year during our sample period.

In terms of spillover effects, Carvalho, Nirei, Saito and Tahbaz-Salehi (2021) studies the impact of the Great East Japan Earthquake of 2011 taking into account the supply chain linkages can be an important transmission mechanism for the propagation and amplification of the disaster impact. They document that the disruption to the disaster-area firms caused by the earthquake also affects the direct and indirect suppliers and customers through input-output linkages, with the effects decreasing by the supply chain distances from the disaster-area firms. In this paper, we explore the spillover effects based on the geographical distances between firms and inundation areas. We find that nearby non-inundated firms are also negatively affected but the effects are much smaller and decrease with distance. On the other hand, neighbouring firms that are further away from the flooding area enjoy output gain starting from the second year after the flooding, indicating evidence that these non-treated firms benefit from the disaster at the cost of the disaster-area firms and this kind of resource reallocation does not occur immediately after the disaster but needs time to accomplish.

2 Data

In this section, we document how we compile the satellite-observed geospatial inundation data, the firm-level data, and the other variables used in the analysis.

2.1 Flood Data

The data on the geospatial flood inundation areas in China for the period studied are derived from the Global Flood Database (GFD) developed by Tellman, Sullivan, Kuhn, Kettner, Doyle, Brakenridge, Erickson and Slayback (2021).[4] Using the flood events catalogued by the Dartmouth Flood Observatory (DFO) as the source for identifying dates and approximate locations, the authors filtered (daily or twice-daily) satellite imagery repositories in these focused areas and applied water detection algorithms to identify the precise inundation area. Care is taken to reduce false detections or omissions. For example, areas are marked as permanent water when the corresponding Landsat observations have water presence throughout the period 1985–2016, and are differentiated from flood extents. Multiday composites of the images are used such that a pixel maintains a water classification if at least half of the observations during the multiday period are detected as water.

For each flood event they successfully mapped, the database provides a raster GeoTIFF image in WGS 84 Geographic Coordinate system with a pixel resolution of 250 meters. The GeoTIFF contains information for each pixel on: (1) whether it is flooded or not; (2) the number of days inundated; (3) the number of cloud-free days; and (4) the proportion of clear observations. We use information on (1) to infer the inundation extent of each flood event. For each raster, we use GIS software to extract the attribute we need and transform the raster to a polygon shapefile, which is then matched with the geocoded firm-level data to identify whether a firm is located in the inundation area or not. We are also able to compute the area of the flood extent for each event through the GIS program.

As shown in Table 1, of the 137 flood events documented by DFO that occurred in China during 2000–2009, GFD successfully mapped 39. Reasons for failure of detection include persistent cloud cover, small or flash floods, inaccurate catalogue locations, complex terrain, etc. For these 39 events, the total affected area estimated by DFO is 20 times as large as the inundation area mapped by GFD (8,844,619 km^2 vs. 442,026 km^2). The large difference in flood extents between these two datasets suggests that the approximate affected areas provided by DFO (compiled largely from government announcements or news reports) overstate the actual inundated areas (based on satellite images). If we were to match the DFO flood area with the geocoded firm-level data, the number of inundated firm-year observations[5] in these 39 flood events would be 47 times lager than based on GFD (516,908 versus 10,658). On the other hand, precisely due to the high-resolution mapping and the application of multiday composite classification, the areas of inundation detected in the GFD database tend to be small, fragmented and discrete. By applying the original mapping, we

[4] http://global-flood-database.cloudtostreet.ai/.

[5] An observation is defined as a firm-year pair.

may run the counter risk of incomplete coverage of the flood events and underestimation of inundated firms. To mitigate these concerns, we enlarge the fragmented inundation areas by including the neighborhoods within 1 km distance from the inundation areas as detected by the GFD. By doing this, the total number of inundated firm-year observations increases by nearly sevenfold from 10,658 to 81,861.

Figure 2 illustrates the mapping of four flood events based on DFO and GFD for year 2002. Panels (A) and (B) suggest that GFD provides a much more precise mapping of the inundation areas of the four respective flood events. Panels (C) and (D) provide a further look into the Hubei province, which was affected by two flood events in 2002. Again, mapping based on DFO would significantly overstate the extent of the inundation areas (where one flood event was shown to affect almost 2/3 of the province's territory), while the GFD mapping matches the natural locations of the water bodies and rivers. Given the inundation areas identified in Panels (A) and (B) by DFO and GFD, respectively, Panels (E) and (F) illustrate the corresponding firm observations that would fall within the inundation areas according to each of the two mappings. We similarly observe a very large overstatement of the mass of the inundated firms based on DFO relative to GFD. Last but not the least, Panel (G) illustrates the geographical distribution of firms that fall within the GFD-identified inundation areas and adjacent neighborhoods of 1 km distance. We see that the mass and density of inundated firms increase as expected, and also extend in a natural pattern from the original sparse distribution, matching the geographical locations of the water bodies and rivers.

Some may argue that firms that are not directly exposed to inundation but located near the flood area can still be taken as affected. We look into this issue below by dividing the observations into 3 groups based on the locations of firms relative to the vicinity of the floods: those located in the areas of inundation identified by the GFD enlarged by 1km (the treatment group), those in non-inundated but adjacent areas within some predetermined distance, and those in the other areas (the control group), and estimate how flood hazards may affect nearby non-flooded firms in a systematic manner.

2.2 Firm-Level Data

The firm-level data we use in this study are the Annual Surveys of Industrial Firms (ASIF) from the National Bureau of Statistics of China (NBS) for the period 2000–2009. As one of the most comprehensive firm-level datasets in China, ASIF is widely used in the literature (e.g., Hsieh and Klenow, 2009; Song, Storesletten and Zilibotti, 2011; Brandt, Van Biesebroeck and Zhang, 2012). The surveys contain all Chinese industrial firms, state-owned or not, with annual sales above 5 million RMB (the "above-scale" firms). Industrial sectors in the dataset are defined to include mining, manufacturing and public utilities. Manufacturing firms account for more than 90% of the observations in the sample. For each firm-year observation, ASIF provides the basic information of the firm (including company name, address, legal person, registration code, phone number, etc) and a wide range of financial metrics (including total output value, value added, employment, fixed asset, and accumulated depreciation, among others).

The information on firms' addresses allows us to locate each of them on the Chinese map. We use the Geocoding API of Amap[6] to convert each firm's address into geographic coordinates, which are then merged with the geospatial inundation maps constructed in Section 2.1 to identify the exposure status of each firm. More importantly, with the coordinates of each firm and geographical information of the inundation regions, we can compute the contemporary distance of each firm from all the flooding areas year by year. This will enable us to explore the spillover effects of floods on neighbouring non-inundated firms.

To construct a panel, we follow the method in Brandt, Van Biesebroeck and Zhang (2012) to link firms across years. In the first step, firms are linked across years by registration code. For remaining firms that are not successfully linked across years in the first step or those with duplicate registration codes, additional information such as corporate name and combinations of "legal person + county code" are further used.[7] We drop observations with missing values for key variables and/or with irregular financial entries according to accounting principles. In particular, we drop observations for which the output or fixed asset is missing or non-positive, or the number of employees is less than 8 (Jefferson, Rawski and Zhang, 2008; Nie, Jiang and Yang, 2012). As a result, we have an unbalanced panel of 2,543,542 firm-year observations spanning the period 2000–2009 with 634,141 unique firms.

To analyze how exposure to floods affects corporate productivity, we use the method of Olley and Pakes (1996) to estimate firm-level productivity. We convert the nominal values of output/value added and capital/investment into real values (in 1998 prices), using province-year specific industrial producer price indices (PPI) and price indices of investment in fixed assets, respectively, according to firms' locations (Lu and Lian, 2012).[8] We allow the production structure to vary across sectors, and hence estimate the output elasticities of capital and labor sector by sector, where sector is defined at the 2-digit level of the GB/T

[6] See `https://lbs.amap.com/api/webservice/guide/api/georegeo` for Amap's developer documentation on Geocoding API.

[7] The combinations of information we use in this paper differ slightly from Brandt, Van Biesebroeck and Zhang (2012), because some of the combinations they used cannot uniquely identify all the firms. See Yang (2015), for example, for further discussions.

[8] Both price indices are also obtained from the NBS of China: `http://www.stats.gov.cn/`.

code, a standard Chinese industry classification system. Due to data constraints (the value added data or the material input data are not reported by ASIF for 2008 and 2009), we can only obtain the firm-level productivity estimates for the period 2000–2007. Thus, the analyses below that are based on productivity will have a shorter panel compared with those based on firm-level output and capital/labor inputs.

2.3 Customs Data

In one set of analyses below in Section 3, we undertake to examine potential heterogeneous effects across firms' trade status, as well as potential impacts of flood hazards on firm-level trade volumes. To do so, we combine the ASIF data with the customs data, obtained from the Chinese Customs Trade Statistics (CCTS) maintained by the General Administration of Customs of China. Each observation in CCTS is the export or import value of a firm-product-month during 2000–2007 and of a firm-product-year during 2008–2009. We first aggregate the customs data to the firm-year level, and then link the observation to the ASIF data using the firm name, phone number and zip code. This provides the yearly export and import values, if any, for the firms in ASIF. A firm is identified as an exporter/importer in a year if it has non-zero export/import value in that year.

3 Estimation Results

Flood hazard causes damage to physical assets or workers, which are inputs for production activities, and it may have long-run adverse impact cause it takes time for firms to rebuild the damaged capital and labor force and restore production. To take into account the dynamic impact of flooding, we run the following regression specification:

$$Y_{ipst} = \beta_0 R0_{i,t} + \beta_1 R0_{i,t-1} + \beta_2 R0_{i,t-2} + \beta_3 R0_{i,\{t-m,m\geq 3\}} + \lambda X_{i,t-1} + \delta_i + \delta_{pt} + \delta_{st} + \varepsilon_{ipst}, \quad (1)$$

where, Y_{ipst} are the dependent variables of interest that can be the natural logarithms of output, total factor productivity, capital, and employment, denoted as y_{ipst}, tfp_{ipst}, k_{ipst} and emp_{ipst} respectively, for firm i located in province p from sector s in year t[9]. $R0_{i,t-k}$, $k \in \{0,1,2\}$, are dummies equal to 1 if firm i was inundated in year $(t-k)$, and β_k are the contemporaneous effect, for $k=0$, and lagged k-year effects, for $k \in \{1,2\}$, of being flooded in year t. $R0_{i,\{t-m,m\geq 3\}}$ equals 1 if firm i was stricken by a flood in periods $(t-m)$ for $m \geq 3$

[9]Note that all the nominal variables in value, such as output and capital stock, are deflated to 1998 national price level in China, as explained in the data section.

and β_3 therefore represents the long-run (3-year onwards) average effect of flood hazard on inundated firms.

We also include control variables that are important determinants of the outcomes of a firm, such as the total asset, the asset structure (Leiter, Oberhofer and Raschky, 2009), and the outcome values in the last period. These controls, however, would be directly affected by the flooding if a firm was inundated in an event. Including them would partially eliminate the explanatory power of flooding (Dell, Jones and Olken, 2014). To avoid this "over-controlling" problem, we use one-period lags of them. Specifically, the controls vector, $X_{i,t-1}$, includes one-period lags of the total asset $asset_{i,t-1}$, share of current asset $sca_{i,t-1}$, and the lags of dependent variables including output $y_{i,t-1}$, capital $k_{i,t-1}$ and employment $emp_{i,t-1}$ (all in logs). One contemporaneous control variable, the log of a firm's age $age_{i,t}$[10] is also included in $X_{i,t-1}$.

In addition, we include various fixed effects to control for potential confounders. Identifying the causal effects of inundation on firms requires that only variation in flood exposure that are randomly assigned to firms can be utilized. Floods, especially river floods, usually have strong spatial patterns. Regions near the main river systems are more prone to floods. To account for the locational differences that are related to flooding, as well as other time-invariant characteristics of firms, we include individual firm fixed effect, δ_i. We also include sector-time [11] fixed effect to control for demand shocks like structural changes during the sample period, and province-time fixed effect to control for policy shocks that are common to all firms within the province and other weather/disaster events, temperature and rainfall for example, at the province level.

Firms that were subject to floods in multiple years during the sample period are excluded when conducting the estimation due to the confusion they may cause in which a firm i with multiple treatments in year t may be at multiple statuses at the same time: For example, it may be flooded in the current period, so that $R0_{i,t} = 1$, but it may also be flooded in the last year, so that $R0_{i,t-1} = 1$ as well. With various trajectories of treatment history for these multiple-treated firms, it is hard, if not impossible, to disentangle the contemporaneous effects of inundation from the lagged effects. Therefore, we only include single-treated and never-treated firms in the sample to proceed the main analyses. We turn to this question from an alternative angle in which we explore the heterogeneous flooding effects on single-treated firms between flood-prone counties and other locations[12]. Finally, the fixed-effect estimator

[10]Firm's age is computed as the difference between the current period and the founding year of the firm. Note that all the variables in the specification have been taken natural logarithms.

[11]Sector in this paper is defined at the China industry classification (CIC) 2-digit code level.

[12]The results for multiple-treated firms have the same pattern as the flooding effects on firms located in the flood-prone counties (available on request).

of the dynamic panel specification would suffer from Nickell bias (see Nickell, 1981) problem. We use Arellano and Bond (1991) method to do the estimation throughout.

Table 2 reports the results for different preliminary specifications. For each outcome variable, we implement 4 regressions to illustrate why we choose the specification in Equation (1). The first column uses $R0_{i,t}$ as the independent variable of interest and the second column uses all post-treatment periods for the treated as the key dummy, which is of the same form as the conventional *DID* variable. The significant differences of the estimates in these two specifications for all the outcomes indicate that the flooding effects persist for years after the flood, rather than just temporary, even if the firm does not encounter any flood thereafter (non-staggered treatment).

The next two columns are similar to *DID* specification but we divide the post-treatment years into separate periods to demonstrate the evolution of the inundation impact. The third column divide the *DID* variable into immediate year and later years, while the last column further estimate the yearly effects of two years after the treatment. The results show that the negative effects of inundation are not uniformly distributed after the flooding. To investigate the dynamic effects of floods on firms, we use the last column specification as the key variables in all our regressions.

The results show that the effects of flooding on corporate input/output and TFP are all negative and long-lasting for firms with single treatment during our sample period. The shrinkage on output and employment and the damage on TFP are even permanent in the sense that the negative coefficients in the long run are all significant for the three outcomes, though the capital seems to be restored to pre-disaster level after two years. For output and TFP, the effects peak in the second year after the flood, from 4.8 percent in the immediate year to 7.2 percent in the second year after the flood and 4.5 percent to 5.2 percent, respectively. For the later years (3rd-year onwards) on average, the damage remains at 6.2% and 4.3%. This means that being inundated once in a flood event would permanently hurt a firm's production activity, which is in stark contrast to the quick recovery (in 2 months) of economic activity (using night lights data as proxy) in city-level after flooding in Kocornik-Mina et al. (2020) and Gandhi et al. (2022).

3.1 Spillover Effects

The aforementioned framework does not take into account the spillover effects of flood events on non-inundated firms, but such spillovers may actually take place. For example, floods may destroy the local infrastructure and all the neighbouring firms that were not directly exposed to inundation but dependent on the damaged transport network would be adversely affected. This would be a negative spillover. Meanwhile, the upstream enterprises that used to purchase input materials from flooded firms may have to source from other non-affected suppliers to keep operation, constituting a positive spillover to the untreated firms. Assuming that spillovers mainly take place in neighbouring regions of flooded areas, we use the distance information of each firm to inundation areas to conduct concentric ring analysis. Specifically, we use 2 km as the bandwidth of a ring and run the following regression to estimate the magnitude of any spillovers:

$$\begin{aligned} Y_{ipst} = & \sum_{k=0}^{10} \left(\beta_{0,Rk} Rk_{i,t} + \beta_{1,Rk} Rk_{i,t-1} + \beta_{2,Rk} Rk_{i,t-2} + \beta_{3,Rk} Rk_{i,\{t-m,m\geq 3\}}\right) \\ & + \lambda X_{i,t-1} + \delta_i + \delta_{pt} + \delta_{st} + \varepsilon_{ipst}, \end{aligned} \tag{2}$$

where $R0_{i,t}$ is defined the same as above and $Rk_{i,t}$ for $k > 0$ is a dummy indicating that firm i is located in the k-th ring, i.e., the distance from the flooding area is between $2(k-1)$ and $2k$ kilometers, in period t. We also examine the dynamic effects by dividing the post-treatment effects into immediate-year effect, lagged 1-year effect, lagged 2-year effect and the average effect of 3-year afterwards. The additional controls and the set of fixed effects are the same as Equation (1).

Table 3 compares the inundation effects when we explicitly control for the neighbouring firms as in Equation (2) with the preliminary results in Equation (1). The effects of being flooded are generally larger in magnitude when we control for spillover effects, though the differences of the effects are insignificant.

Figure 3 plots the effects of flooding for firms located in each ring. Panel (A) illustrates the contemporaneous effects on inundated and neighbouring firms. All the inundated firms and non-inundated firms within 12 kilometres from the inundation area suffer from fixed asset losses in the immediate year of flooding, but the output and productivity are significantly affected only for those located within 6 kilometres, with the effects much smaller than the effects for inundated firms and decreasing with distance.

One year after the occurrence of flood, the pattern remains the same for output and employment, while the productivity of all non-inundated firms and the capital of firms outside the third ring restore to normality, as shown in Panel (B). Panel (C) and (D) report the lagged 2-year and longer-run effects. Firms located in ring 3 and ring 4 have increased their output to normal level and firms in further rings (5th-9th ring) even start to outperform their counterparts in output by around 2% after two years, and this trend persists in later years.

To sum up, the flooding effects spill over to surrounding firms that are not directly exposed to the flood. More importantly, the spillover effects on the neighbouring firms are differential depending on their distances from the inundation area: Firms that are close to the flooding area (within 4km) are also negatively affected but with a much smaller effect than the inundated firms (2% vs. 6%) and can recover after three years; Firms that are further away (between 6–18km) start to benefit from the second year after the flood. The latter spillovers contribute to the long-run shrinkage of the inundated firms. In the short run, inundated firms are mainly subject to the direct flooding effects. In the longer run, these firms are additionally affected by the indirect effects: their market shares are partially taken over by surrounding non-inundated firms so that they cannot recover to pre-disaster level.

Besides the significant estimates of the effects on adjacent firms, another point worth noting is that the estimated coefficients of inundation are generally larger in magnitude for the immediate year and one year after the flood when we exclude the surrounding firms from the control group in this concentric ring specification than in Equation (1), a reinforcing evidence of spillover effects, as shown in Table 3. As such, we explicitly control for these neighbouring firms within 10 rings (R1-10) from the flooding area in the estimation as our baseline specification.

3.2 Moderating Factors

Being hit by a flood could have different impacts on firms with different characteristics, operating in different locations, and in different sectors. With the various characteristic information of each firm provided in the ASIF and CCTS databases, including the asset structure, ownership and location information, export/import status, and the sector it belongs to, we are able to explore the heterogeneity in the inundation impacts. All these tests are conducted with the subsample of single-treated firms using the same set of controls, including the spillover control, and fixed effects as in the baseline specification.

Tangibility of assets: Tangible assets, defined as the fixed assets and inventory in this paper, are potentially more exposed to physical destruction. Firms with intensive tangible assets thus may be more vulnerable in a flood event. We test this hypothesis by checking the coefficients on the interactions of the treatment dummies and one binary indicating the intensity of a firm's tangible assets, $Tangibility_i$. We say a firm i is tangible-intensive in year t if its share of tangible assets is above the 90 percentile across all firms in that year and define $Tangibility_i$ as equal to 1 if firm i is tangible-intensive for at least half of the time for which it appears in our sample. For example, firm j appears in our sample for 6 years, then $Tangibility_j$ is equal to 1 if it is tangible-intensive in at least 3 years and 0 otherwise.

The results are reported in Table 4. As expected, the coefficients of the interactions for capital, TFP and output are mostly negative, implying that firms with more intensive tangible assets suffer more loss in capital (additional 3-12 percent) and consequently their TFP and output are more affected relative to firms with non-intensive tangibles. The additional losses on output and TFP for these tangible-intensive firms tend to be nonpermanent, though their capital cannot restore to pre-disaster level as their counterparts would do.

Ownership: As state-owned enterprises (SOEs) in China generally owns larger share of tangible assets, we expect that SOEs are also more negatively affected by flooding. We utilize information on a firm's registered type in ASIF to explore the heterogeneous impacts of inundation between SOEs and non-SOEs.

Table 5 presents the results. A firm may change its ownership type during the sample period, so the ownership dummy $SOE_{i,t}$ is not time-invariant but defined at the firm-year level. From the coefficient estimates, SOEs generally own more capital and employment but produce less output with much lower TFP, compared to non-SOEs. Reassuring, the coefficients for the interactions are mostly negative and of the same pattern as the results for tangibility in Table 4, because SOEs are also tangible-intensive relative to non-SOEs on average. The magnitudes, however, are much larger on SOEs for output and TFP. It means that SOEs are more affected in the longer run, beyond the excess damage due to tangibility. This may be attributed to the fact that SOEs in China have a role of maintaining social stability given by the government and are less incentivized for production (Bai, Lu and Tao, 2006), hence they operate inefficiently and perform worse in the aftermath of a flood relative to non-SOEs.

Flood-prone counties: Governments have incentive to invest more on public flood control facilities in flood-prone areas. Firms may also take more adaptive investments if they expect recurrent flooding strikes. Hence it is plausible to assume that firms located in flood-prone areas would have performed differently after inundation compared to those who are unexpectedly hit by a flood.

$ProneCounty_c$ is a dummy equal to 1 if county c was hit by floods for more than 5 times during 2000–2014[13]. Then the coefficients of the interactions of the treatment dummies $R0$ and $ProneCounty_c$ represent the differential inundation effects on firms located in flood-prone counties relative to other firms. We note that all the flooded firms are single-treated

[13] As shown in Figure 2, the areas of inundation are small, fragmented and spanning to different provinces. A county is identified as flooded in one year if parts of it are inundated in that year. During 2000–2014, 785 counties were ever stricken by a flood, in which 36 counties (5%) encountered more than 5 floods. The maximum number of floods a county may experience is 11.

here, i.e., firms that are subject to multiple floods, in or out of the flood-prone counties, are excluded from the sample.

As shown in Table 6, all the coefficients of the interaction terms are positive and most are significant, meaning that firms in the flood-prone counties are considerably less affected in the aftermath of a flood. Compared to the permanent shrinkage of an average single-treated firm in the baseline specification, all these firms with higher flooding risk can recover or even acquire higher productivity than pre-disaster level after the flood. This result also indicates that the overall baseline estimates mask important heterogeneous effects across different firms.

Exporter/Importer: We identify a firm as an exporter/importer if it has export/import records in the database of the Chinese Customs Trade Statistics. We include the interaction terms of the exporter/importer indicator, $Ex/Importer_{i,t}$, with the treatment variables to check the inundation effects on exporters/importers relative to non-exporters/-importers.

The results are reported in Table 7. The coefficients on $Ex/Importer_{i,t}$ indicate that exporters/importers generally have more capital and employment, higher TFP, and hence higher output. They perform better in the first two years after the flooding, but worse in later years in terms of output, relative to non-exporters/-importers. The widening losses of inundated exporters across time is consistent with the pattern in the baseline results: The market share of inundated exporters partially flows to neighbouring non-inundated exporters and nonexporters after two years since the inundation. For inundated exporters, they not only lose market share in domestic market, but also in the international market. This is supported by the results of the experiment in which we investigate the inundation effects on exports and imports, as shown in Table 8.

Sector: Finally, we examine the heterogeneous effects across different sectors. We merge the 40 2-digit CIC code sectors into 13 sectors according to the relevance first and then run the baseline regressions but without sector-year fixed effect sector by sector. The results are reported in Table 9.

The negative and long-lasting impacts of inundation on output are universal for all sectors, though the effects are insignificant for other manufacture and two non-manufacturing sectors, utilities and mining.

Consistent with the baseline results and the results for tangibility, firms in sectors with heavy fixed assets or inventory, such as recycle and repair, automobiles and transport equipments, machinery and food sectors, suffer more and cannot restore to pre-disaster level in the aftermath of flooding.

3.3 Effects on Firm Entry/Exit

People may adapt by migrating away from flood-prone areas[14]. Floods may also affect the locational choice of individual firms and even force the severely damaged ones to exit the market. To investigate the impact of flood events on the entry and exit rates of local firms[15], we aggregate the firm-level data into county level and check how the number of firms are affected in the flooded counties[16].

$$Y_{crt} = \sum_{j,j\in\{0,1\}} \left(\beta_{0,bj} R0\_binj_{c,t} + \beta_{1,bj} R0\_binj_{c,t-1} + \beta_{2,bj} R0\_binj_{c,t-2} + \beta_{3,bj} R0\_binj_{c,\{t-m,m\geq 3\}}\right) + \delta_c + \delta_{rt} + \varepsilon_{crt}, \tag{3}$$

where the dependent variables are the exit/entry rate or the logarithms of the number of exit/entry firms of county c in prefecture r at period t. We divide the flooded counties, i.e., at least one firm is exposed to flooding in these counties, into 2 bins according to the number of inundated firms in the county to check the differential effects of floods on counties with different degree of inundation. So $R0\_bin0_{c,t}$ is equal to 1 if county c has 1–20 firms that are exposed to inundation in year t and 0 otherwise. Similarly, $R0\_bin1_{c,t}$ is a binary variable that equals 1 when there are more than 20 inundated firms in county c at period t. As in the baseline, we also estimate the lagged 1-year, lagged 2-year, and long-run effects of flooding on the entry/exit behaviour of the treated counties. We include the county fixed effect δ_c to control for any time-invariant characteristics of counties and the prefecture-time fixed effect δ_{rt} to control for higher administrative level shocks that are common to the counties in that prefecture.

The results are reported in Table 10. As expected, the exit (rate of) firms in a county would increase in the following years after the county was hit by a flood, and the entry (rate of) firms would decrease, starting from the next year after the flood, in the inundated county. In addition, the coefficients for bin 1 counties are larger than those for bin 0 counties, indicating that the impact is positively correlated with the severity of inundation in the county. The results are robust if we include the number of firms in the county as an additional

[14] Gandhi et al. (2022) finds that the population growth is smaller in cities that experienced higher frequency of flood events in a global scope.

[15] Here due to data availability we only consider the "above-scale" firms in ASIF, i.e., all SOEs and non-SOEs with annual sales above 5 million RMB. In this sense the entry and exit behaviour of a firm means the entry to and exit from the ASIF database.

[16] After linking all the firms across years during 1998–2013, the entry and exit years of a firm are defined as the first and last year it exists in the sample. We assume that a firm is operating throughout even if it is missing in some year between (exit and re-enter the sample). Finally we obtain the county panel from 2000 to 2009 by aggregating the number of entry/exit firms at the county-year level.

control.

4 Validity Checks

We next conduct a series of checks regarding to the following concerns to test the robustness of the inundation effects estimated in our baseline specification.

Relocation: Firms may relocate to other locations after being inundated in a flood. The outcome changes for these firms may be different from the performance changes of the inundated firms who do not change their locations, which are of our main interest in this paper. To rule out the potential confounding effects posed by these firms, we exclude firms that change their locations[17] during our sample period and check the robustness of our baseline results.

Similar concerns emerge in cases where a firm just moves to the location recently before it is stricken by a flood from somewhere else, possibly flooded areas. These firms may behave and perform differently from the firms of our main focus in which they have operated in a fixed location for years before the hit of flooding and are not forced to liquidate or exit the market after the flood. Including them in the estimation thus would potentially confound our estimates. We check whether the baseline results are robust by restricting the sample to the "qualified" firms.

The results for different subsamples are all reported in Table 11. The baseline pattern in which firms that are unexpectedly hit by a flood suffer perpetual losses and operate in a smaller scale in the aftermath of the flood persists in all situations, with generally larger magnitudes for the dynamic effects but still overlapping confidence intervals. These exercises suggest that our baseline results for the dynamic inundation effects are robust and not biased by firms' relocation behaviour.

5 Conclusion

A key challenge in identifying the causal effects of floods on individual firms is to measure the actual incidence of flooding, which requires the match of the flooding data and firm data in high spatial resolution. The inundation extent of one flood event can only be precisely measured from remote sensing instruments, while firms' operating addresses must be geographically codable so that they can be matched with flooding maps. This article is the first to identify the flood exposure directly at the disaggregated firm level by merging the

[17]We round up firms' coordinates (latitudes and longitudes) to 2 decimal places, which permit an error of 1.11 kilometres, and then define a firm as of fixed location if its coordinates are the same across years.

satellite-observed inundation maps with the GPS geocoded firm locations. We are thus able to use this novel dataset to study the impacts of floods on firm performances in China from 2000 to 2009.

We find that on average, a firm is subject to long-run shrinkage in production capacity and productivity, with the effects being 6% and 5%, respectively, if it was stricken by a flood unexpectedly. The flooding effects also spill over to neighbouring firms that are not directly exposed to floods in different ways. Firms that are close, within 4 kilometres, to flooding areas are also negatively affected but with a much smaller magnitude and they can recover to pre-disaster level in three years, while further firms, between 6 and 18 kilometres, are not significantly affected in the first two years and start to increase their production thereafter. It implies that in addition to the direct flooding damages in the short run, the inundated firms are further subject to the indirect effects posed by non-inundated firms, contributing to their shrinkage in the long run.

Factors that determine the extents of the negative inundation effects include asset structure and firms' locations: Firms with more intensive tangible assets, which are potentially more exposed to physical destruction, are more affected. The effects on firms located in flood-prone counties, on the other hand, are minor and temporary, providing evidence of better adaptation in these areas and firms.

Being stricken by a flood also deters the entry of new firms and increases the death rates of incumbent firms in the local place. By aggregating the firm-level data to county level, we find that the exit rate in the severely flooded counties rises by 1-2 percent in the immediate year and following two years, while the entry rate drops down by 1.6-3.5 percent in the next three years after the flood.

Kocornik-Mina, McDermott, Michaels and Rauch (2020) and Gandhi, Kahn, Kochhar, Lall and Tandel (2022) find that flooded cities can recover the economic activities to pre-disaster level within a year. Our study, however, finds that inundated firms in non-flood-prone areas are subject to permanent shrinkage in productivity and production activity. The stark contrast between the city-level and the firm-level outcomes demonstrates that identifying the causal effects of floods in large geographical scale could mask important micro-level impacts.

Lastly, we note that the estimates we get are still conservative in the sense that the GFD just successfully mapped one third of all the flood events during the study period and some inundated firms may be misclassified into the control group, causing attenuation bias as a result. Meanwhile, since we aggregate floods[18] within a year due to the need for temporal

[18] The aggregation of flood events in a year is like taking the union of the flooding areas within a year. The distances between firms and the flooding area in one year are also calculated based on the aggregated

match between flood data and firm data and use binary variables to measure the flooding exposure, the impact of the intensity or severity of the flood cannot be explored. We leave these measurement issues to future research.

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Table 1: Flooding Area Data in DFO and GFD

		DFO			GFD			GFD vs. DFO (For Events Doc. In GFD)		GFD + Neighboring Firms Within 1km
Year	# Firms	# Floods	Inun. Area (km^2)	# Inun. Firms	# Floods	Inun. Area (km^2)	# Inun. Firms	Inun. Area in DFO (km^2)	# Inun. Firms in DFO	# Inun. Firms
2000	153,906	8	446,864	20,572	2	5,027	65	107,763	3,090	894
2001	163,758	8	99,449	2,581	-	-	-	-	-	-
2002	174,686	22	1,859,656	71,009	4	46,865	767	702,551	60,489	8,910
2003	190,783	14	3,248,970	71,879	5	113,429	1,704	2,359,691	69,221	14,806
2004	266,212	15	733,578	37,796	3	19,131	862	258,014	18,792	7,948
2005	267,176	18	3,289,300	129,895	9	103,850	3,888	1,152,691	78,542	16,670
2006	296,970	23	1,271,760	46,643	5	29,105	2,851	206,147	4,651	10,194
2007	332,714	11	3,343,944	197,364	7	86,028	415	3,041,902	189,929	14,777
2008	365,388	12	1,347,647	95,289	4	38,591	106	1,015,861	92,194	7,662
2009	331,949	6	1,139,055	55,129	-	-	-	-	-	-
Total	**2,543,542**	**137**	**16,780,222**	**728,157**	**39**	**442,026**	**10,658**	**8,844,619**	**516,908**	**81,861**

Notes: The second column documents the number of firms in ASIF database from 2000 to 2009. The next three columns under "DFO" report the number of flood events, the total areas of flooding-affected regions, and the number of firms located in these regions for each year during our sample period, based on the flood data provided in DFO. The next three columns under "GFD" describe the corresponding statistics for the successfully mapped flood events in GFD, which use the flood events documented in DFO as mapping catalogue and then apply water detection algorithm on satellite images to produce inundation maps. The next two columns under "GFD vs. DFO" report the total areas of inundation and the number of inundated firms for the successfully mapped flood events in GFD if we use the data provided in DFO. For example, in 2002, GFD successfully mapped 2 flood events out of the total 8 events documented in DFO, with the total inundation area being 5,027 km^2 and the number of firms located in these area being 65; On the other hand, for the same 2 flood events, the flooding area provided in DFO is 107,763 km^2 and the resulting number of inundated firms is 3,090. The last column reports the number of firms in every year when we include both the inundated firms, using the inundation maps in GFD, and the neighbouring firms who are located within 1 kilometre from the inundation area.

Table 2: Preliminary Specifications

	y				k				emp				tfp			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
$R0_{i,t}$	-0.0181***		-0.0475***	-0.0476***	-0.0065		-0.0123**	-0.0122**	-0.0057*		-0.0159***	-0.0158***	-0.0342***		-0.0450***	-0.0454***
	(0.0035)		(0.0043)	(0.0043)	(0.0050)		(0.0062)	(0.0062)	(0.0030)		(0.0037)	(0.0037)	(0.0058)		(0.0068)	(0.0068)
$R0_{i,t-1}$				-0.0572***				-0.0110				-0.0199***				-0.0257***
				(0.0048)				(0.0069)				(0.0042)				(0.0086)
$R0_{i,t-2}$				-0.0721***				-0.0214***				-0.0175***				-0.0518***
				(0.0053)				(0.0076)				(0.0046)				(0.0096)
$R0_{i,\{t-m,m\geq 3\}}$				-0.0621***				-0.0069				-0.0136**				-0.0428***
				(0.0063)				(0.0089)				(0.0054)				(0.0113)
$R0_{i,\{t-m,m\geq 0\}}$		-0.0487***				-0.0115*				-0.0158***				-0.0450***		
		(0.0044)				(0.0062)				(0.0038)				(0.0069)		
$R0_{i,\{t-m,m\geq 1\}}$			-0.0577***				-0.0113				-0.0201***				-0.0242***	
			(0.0049)				(0.0070)				(0.0042)				(0.0087)	
Lagged y	0.2912***	0.2911***	0.2911***	0.2914***	0.0058	0.0058	0.0059	0.0062*	0.0052**	0.0052**	0.0052**	0.0053**				
	(0.0026)	(0.0026)	(0.0026)	(0.0026)	(0.0036)	(0.0036)	(0.0036)	(0.0037)	(0.0022)	(0.0022)	(0.0022)	(0.0022)				
Lagged k	-0.0326***	-0.0325***	-0.0324***	-0.0324***	0.3306***	0.3307***	0.3307***	0.3307***	-0.0024*	-0.0024*	-0.0023*	-0.0023*	-0.0957***	-0.0955***	-0.0956***	-0.0954***
	(0.0016)	(0.0016)	(0.0016)	(0.0016)	(0.0023)	(0.0023)	(0.0023)	(0.0023)	(0.0014)	(0.0014)	(0.0014)	(0.0014)	(0.0031)	(0.0031)	(0.0031)	(0.0031)
Lagged emp	0.1104***	0.1107***	0.1108***	0.1109***	0.1065***	0.1066***	0.1066***	0.1067***	0.4836***	0.4837***	0.4837***	0.4837***	-0.0053	-0.0049	-0.0051	-0.0046
	(0.0027)	(0.0027)	(0.0027)	(0.0027)	(0.0039)	(0.0039)	(0.0039)	(0.0039)	(0.0024)	(0.0024)	(0.0024)	(0.0024)	(0.0059)	(0.0059)	(0.0059)	(0.0059)
Lagged tfp													0.1178***	0.1178***	0.1178***	0.1179***
													(0.0022)	(0.0022)	(0.0022)	(0.0022)
Lagged asset	0.2161***	0.2158***	0.2158***	0.2159***	0.2655***	0.2655***	0.2655***	0.2657***	0.0968***	0.0967***	0.0967***	0.0968***	0.1375***	0.1375***	0.1374***	0.1377***
	(0.0030)	(0.0030)	(0.0030)	(0.0030)	(0.0043)	(0.0043)	(0.0043)	(0.0043)	(0.0026)	(0.0026)	(0.0026)	(0.0026)	(0.0069)	(0.0069)	(0.0069)	(0.0070)
Lagged sca	0.0445***	0.0445***	0.0445***	0.0445***	-0.0410***	-0.0410***	-0.0410***	-0.0411***	0.0232***	0.0232***	0.0232***	0.0232***	0.0737***	0.0738***	0.0737***	0.0738***
	(0.0019)	(0.0019)	(0.0019)	(0.0019)	(0.0028)	(0.0028)	(0.0028)	(0.0028)	(0.0017)	(0.0017)	(0.0017)	(0.0017)	(0.0038)	(0.0038)	(0.0038)	(0.0038)
age	-0.0140***	-0.0140***	-0.0140***	-0.0140***	0.0050**	0.0050**	0.0050**	0.0050**	0.0060***	0.0060***	0.0060***	0.0060***	-0.0003	-0.0003	-0.0003	-0.0003
	(0.0014)	(0.0014)	(0.0014)	(0.0014)	(0.0020)	(0.0020)	(0.0020)	(0.0020)	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0025)	(0.0025)	(0.0025)	(0.0025)
Observations	1,255,386	1,255,386	1,255,386	1,255,386	1,255,386	1,255,386	1,255,386	1,255,386	1,255,386	1,255,386	1,255,386	1,255,386	808,893	808,893	808,893	808,893
Number of Panel_id	350,444	350,444	350,444	350,444	350,444	350,444	350,444	350,444	350,444	350,444	350,444	350,444	270,569	270,569	270,569	270,569
Control for Spillovers (R1-10)	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Sector×Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Province×Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firms of Single Treatment	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firms of Multiple Treatments	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO
Sample Period	2000-09	2000-09	2000-09	2000-09	2000-09	2000-09	2000-09	2000-09	2000-09	2000-09	2000-09	2000-09	2000-07	2000-07	2000-07	2000-07

Notes: The table reports the estimation results of four different specifications for each of the four dependent variables: output, capital, employment and TFP (all in logarithms). For each dependent variable, the first column reports the results if we only use treatment dummies $R0_{i,t}$, which are equal to 1 if firm i is inundated in year t. The second column uses a DID-like dummy $R0_{i,\{t-m,m\geq 0\}}$, which equals 1 for inundated firm i in all post-treatment years. The third column divides $R0_{i,\{t-m,m\geq 0\}}$ into $R0_{i,t}$ and $R0_{i,\{t-m,m\geq 1\}}$, i.e., it divides the post-treatment periods into immediate year of treatment and later years. The last column further divides the post-treatment periods into 4 intervals: immediate year of treatment $R0_{i,t}$, one year after $R0_{i,t-1}$, two years after $R0_{i,t-2}$, and later years $R0_{i,\{t-m,m\geq 3\}}$. Variables below the key dummies are the controls that we use throughout this paper. We use Arellano-Bond method and include firm, sector-year and province-year fixed effects in all the specifications. The sample we use excludes firms with multiple treatments. We can only compute firms' TFP for the period 2000-2007 because of data availability, so the sample period for productivity is from 2000 to 2007. Standard errors are reported in parentheses under the estimates. Asterisks ***/**/* denote $p < 0.01$, $p < 0.05$, $p < 0.1$, respectively.

Table 3: Concentric Ring Analysis: Inundation Effects

	y		k		emp		tfp	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Control for Spillovers	YES	NO	YES	NO	YES	NO	YES	NO
$R0_{i,t}$	-0.0548***	-0.0476***	-0.0260***	-0.0122**	-0.0176***	-0.0158***	-0.0562***	-0.0454***
	(0.0046)	(0.0043)	(0.0066)	(0.0062)	(0.0040)	(0.0037)	(0.0074)	(0.0068)
$R0_{i,t}$	-0.0657***	-0.0572***	-0.0166**	-0.0110	-0.0255***	-0.0199***	-0.0220**	-0.0257***
	(0.0051)	(0.0048)	(0.0072)	(0.0069)	(0.0044)	(0.0042)	(0.0090)	(0.0086)
$R0_{i,t}$	-0.0733***	-0.0721***	-0.0173**	-0.0214***	-0.0148***	-0.0175***	-0.0501***	-0.0518***
	(0.0054)	(0.0053)	(0.0077)	(0.0076)	(0.0047)	(0.0046)	(0.0098)	(0.0096)
$R0_{i,\{t-m,m\geq 3\}}$	-0.0565***	-0.0621***	-0.0055	-0.0069	-0.0103*	-0.0136**	-0.0444***	-0.0428***
	(0.0063)	(0.0063)	(0.0090)	(0.0089)	(0.0054)	(0.0054)	(0.0113)	(0.0113)
Observations	1,255,386	1,255,386	1,255,386	1,255,386	1,255,386	1,255,386	808,893	808,893
Number of Panel_id	350,444	350,444	350,444	350,444	350,444	350,444	270,569	270,569
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES
Sector×Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Province×Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Firms of Single Treatment	YES	YES	YES	YES	YES	YES	YES	YES
Firms of Multiple Treatments	NO	NO	NO	NO	NO	NO	NO	NO
Sample Period	2000-09	2000-09	2000-09	2000-09	2000-09	2000-09	2000-07	2000-07

Notes: The table compares the dynamic inundation effects when we explicitly control for surrounding firms within 20 kilometres with the preliminary results in Table 2. For each dependent variable, the first column reports the estimates of the dynamic inundation effects when we include the firms in the neighbouring 10 rings in the regression, while the second one reports the preliminary results when we do not control for the neighbouring firms. $R0_{i,g}$ is equal to 1 if firm i is inundated in year g, thus the coefficients for $R0_{i,t}$, $R0_{i,t-1}$, $R0_{i,t-2}$, and $R0_{i,\{t-m,m\geq 3\}}$ can be interpreted as contemporaneous effect, 1-year lagged effect, 2-year lagged effect, and long-run (3-year onwards) lagged effect of inundation, respectively. The coefficients for the neighbouring firms and control variables are omitted here. We use Arellano-Bond method and include firm, sector-year and province-year fixed effects in all the specifications. We can only compute firms' TFP for the period 2000-2007 because of data availability. Standard errors are reported in parentheses under the estimates. Asterisks ***/**/* denote $p < 0.01$, $p < 0.05$, $p < 0.1$, respectively.

Table 4: Heterogeneous Effects by Asset Structure

	y	k	emp	tfp
	(1)	(2)	(3)	(4)
$R0_{i,t}$	-0.0491***	-0.0228***	-0.0178***	-0.0453***
	(0.0047)	(0.0067)	(0.0041)	(0.0076)
$R0_{i,t-1}$	-0.0604***	-0.0078	-0.0231***	-0.0156*
	(0.0052)	(0.0074)	(0.0045)	(0.0092)
$R0_{i,t-2}$	-0.0704***	-0.0095	-0.0143***	-0.0498***
	(0.0056)	(0.0079)	(0.0048)	(0.0101)
$R0_{i,\{t-m,m\geq3\}}$	-0.0578***	0.0043	-0.0115**	-0.0468***
	(0.0065)	(0.0092)	(0.0056)	(0.0116)
$R0_{i,t} \times Tangibility_i$	-0.0434***	-0.0341	0.0139	-0.0489**
	(0.0153)	(0.0218)	(0.0132)	(0.0239)
$R0_{i,t-1} \times Tangibility_i$	-0.0530***	-0.0696***	-0.0159	-0.0575*
	(0.0174)	(0.0248)	(0.0150)	(0.0296)
$R0_{i,t-2} \times Tangibility_i$	-0.0367*	-0.0786***	0.0028	0.0071
	(0.0189)	(0.0270)	(0.0164)	(0.0342)
$R0_{i,\{t-m,m\geq3\}} \times Tangibility_i$	-0.0228	-0.1238***	0.0074	0.0324
	(0.0214)	(0.0306)	(0.0185)	(0.0415)
Observations	1,255,386	1,255,386	1,255,386	808,893
Number of Panel_id	350,444	350,444	350,444	270,569
Control for Spillovers (R1-10)	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Sector×Year FE	YES	YES	YES	YES
Province×Year FE	YES	YES	YES	YES
Firms of Single Treatment	YES	YES	YES	YES
Firms of Multiple Treatments	NO	NO	NO	NO
Sample Period	2000-09	2000-09	2000-09	2000-07

Notes: The table reports the heterogeneous effects among firms with different intensity of tangible assets. $R0_{i,g}$ is equal to 1 if firm i is inundated in year g, thus the coefficients for $R0_{i,t}$, $R0_{i,t-1}$, $R0_{i,t-2}$, and $R0_{i,\{t-m,m\geq3\}}$ can be interpreted as contemporaneous effect, 1-year lagged effect, 2-year lagged effect, and long-run (3-year onwards) lagged effect of inundation, respectively. $Tangibility_i$ is equal to 1 if firm i is tangible-intensive for at least half of the time for which it appears in the sample. A firm i is said to be tangible-intensive in year t if its share of tangible assets in total assets is above the 90 percentile across all firms in that year. Tangible assets refers to the fixed assets and inventory. We explicitly include neighbouring non-inundated firms within 20 kilometres from the inundation areas (R1-10) in all the regressions to control for spillover effects. We use Arellano-Bond method and include firm, sector-year and province-year fixed effects in all the specifications. We can only compute firms' TFP for the period 2000-2007 because of data availability. Standard errors are reported in parentheses under the estimates. Asterisks ***/**/* denote $p < 0.01$, $p < 0.05$, $p < 0.1$, respectively.

Table 5: Heterogeneous Effects by Ownership Structure

	y	k	emp	tfp
	(1)	(2)	(3)	(4)
$R0_{i,t}$	-0.0472***	-0.0221***	-0.0163***	-0.0457***
	(0.0048)	(0.0069)	(0.0042)	(0.0077)
$R0_{i,t-1}$	-0.0584***	-0.0090	-0.0207***	-0.0145
	(0.0053)	(0.0075)	(0.0046)	(0.0094)
$R0_{i,t-2}$	-0.0664***	-0.0106	-0.0113**	-0.0423***
	(0.0056)	(0.0080)	(0.0049)	(0.0103)
$R0_{i,\{t-m,m\geq 3\}}$	-0.0510***	0.0019	-0.0087	-0.0385***
	(0.0065)	(0.0093)	(0.0056)	(0.0118)
$R0_{i,t} \times SOE$	-0.0394***	-0.0252	-0.0034	-0.0269
	(0.0118)	(0.0168)	(0.0102)	(0.0188)
$R0_{i,t-1} \times SOE$	-0.0520***	-0.0331	-0.0370***	-0.0509**
	(0.0146)	(0.0208)	(0.0126)	(0.0243)
$R0_{i,t-2} \times SOE$	-0.0648***	-0.0432*	-0.0250	-0.0757**
	(0.0178)	(0.0253)	(0.0153)	(0.0306)
$R0_{i,\{t-m,m\geq 3\}} \times SOE$	-0.0872***	-0.0761***	-0.0183	-0.0614
	(0.0204)	(0.0291)	(0.0176)	(0.0381)
$SOE_{i,t}$	-0.0293***	0.0651***	0.0306***	-0.0634***
	(0.0058)	(0.0083)	(0.0050)	(0.0096)
Observations	1,255,386	1,255,386	1,255,386	808,893
Number of Panel_id	350,444	350,444	350,444	270,569
Control for Spillovers (R1-10)	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Sector×Year FE	YES	YES	YES	YES
Province×Year FE	YES	YES	YES	YES
Firms of Single Treatment	YES	YES	YES	YES
Firms of Multiple Treatments	NO	NO	NO	NO
Sample Period	2000-09	2000-09	2000-09	2000-07

Notes: The table reports the heterogeneous effects among firms with different ownership structure. $R0_{i,g}$ is equal to 1 if firm i is inundated in year g, thus the coefficients for $R0_{i,t}$, $R0_{i,t-1}$, $R0_{i,t-2}$, and $R0_{i,\{t-m,m\geq 3\}}$ can be interpreted as contemporaneous effect, 1-year lagged effect, 2-year lagged effect, and long-run (3-year onwards) lagged effect of inundation, respectively. $SOE_{i,t}$ is equal to 1 if firm i is state-owned in period t. We explicitly include neighbouring non-inundated firms within 20 kilometres from the inundation areas (R1-10) in all the regressions to control for spillover effects. We use Arellano-Bond method and include firm, sector-year and province-year fixed effects in all the specifications. We can only compute firms' TFP for the period 2000-2007 because of data availability. Standard errors are reported in parentheses under the estimates. Asterisks ***/**/* denote $p < 0.01$, $p < 0.05$, $p < 0.1$, respectively.

Table 6: Heterogeneous Effects by Locations

	y	k	emp	tfp
	(1)	(2)	(3)	(4)
$R0_{i,t}$	-0.0556***	-0.0303***	-0.0182***	-0.0521***
	(0.0048)	(0.0069)	(0.0042)	(0.0077)
$R0_{i,t-1}$	-0.0696***	-0.0141*	-0.0258***	-0.0331***
	(0.0054)	(0.0077)	(0.0047)	(0.0096)
$R0_{i,t-2}$	-0.0850***	-0.0235***	-0.0162***	-0.0540***
	(0.0058)	(0.0083)	(0.0050)	(0.0106)
$R0_{i,\{t-m,m\geq 3\}}$	-0.0742***	-0.0109	-0.0154***	-0.0664***
	(0.0068)	(0.0097)	(0.0059)	(0.0126)
$R0_{i,t} \times ProneCounty_c$	0.0251**	0.0405**	0.0117	0.0165
	(0.0120)	(0.0171)	(0.0103)	(0.0187)
$R0_{i,t-1} \times ProneCounty_c$	0.0346***	0.0117	0.0117	0.0814***
	(0.0134)	(0.0191)	(0.0116)	(0.0229)
$R0_{i,t-2} \times ProneCounty_c$	0.0743***	0.0544***	0.0150	0.0327
	(0.0148)	(0.0211)	(0.0128)	(0.0256)
$R0_{i,\{t-m,m\geq 3\}} \times ProneCounty_c$	0.0884***	0.0405*	0.0280**	0.1002***
	(0.0164)	(0.0235)	(0.0142)	(0.0274)
Observations	1,255,386	1,255,386	1,255,386	808,893
Number of Panel_id	350,444	350,444	350,444	270,569
Control for Spillovers (R1-10)	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Sector×Year FE	YES	YES	YES	YES
Province×Year FE	YES	YES	YES	YES
Firms of Single Treatment	YES	YES	YES	YES
Firms of Multiple Treatments	NO	NO	NO	NO
Sample Period	2000-09	2000-09	2000-09	2000-07

Notes: The table reports the heterogeneous effects among firms with different locations. $R0_{i,g}$ is equal to 1 if firm i is inundated in year g, thus the coefficients for $R0_{i,t}$, $R0_{i,t-1}$, $R0_{i,t-2}$, and $R0_{i,\{t-m,m\geq 3\}}$ can be interpreted as contemporaneous effect, 1-year lagged effect, 2-year lagged effect, and long-run (3-year onwards) lagged effect of inundation, respectively. $ProneCounty_c$ is a dummy equal to 1 if county c was hit by floods for more than 5 times during 2000–2014 according to GFD. We explicitly include neighbouring non-inundated firms within 20 kilometres from the inundation areas (R1-10) in all the regressions to control for spillover effects. We use Arellano-Bond method and include firm, sector-year and province-year fixed effects in all the specifications. We can only compute firms' TFP for the period 2000-2007 because of data availability. Standard errors are reported in parentheses under the estimates. Asterisks ***/**/* denote $p < 0.01$, $p < 0.05$, $p < 0.1$, respectively.

Table 7: Heterogeneous Effects between Ex/Importers and Non-ex/importers

	y		k		emp		tfp	
	Exporter	Importer	Exporter	Importer	Exporter	Importer	Exporter	Importer
$R0_{i,t}$	-0.0537***	-0.0548***	-0.0265***	-0.0283***	-0.0174***	-0.0189***	-0.0488***	-0.0484***
	(0.0049)	(0.0048)	(0.0070)	(0.0069)	(0.0042)	(0.0042)	(0.0079)	(0.0078)
$R0_{i,t-1}$	-0.0677***	-0.0679***	-0.0105	-0.0129*	-0.0227***	-0.0250***	-0.0258***	-0.0253***
	(0.0054)	(0.0053)	(0.0077)	(0.0076)	(0.0047)	(0.0046)	(0.0095)	(0.0094)
$R0_{i,t-2}$	-0.0699***	-0.0696***	-0.0129	-0.0170**	-0.0119**	-0.0141***	-0.0515***	-0.0488***
	(0.0058)	(0.0057)	(0.0083)	(0.0081)	(0.0050)	(0.0049)	(0.0105)	(0.0103)
$R0_{i,\{t-m,m\geq 3\}}$	-0.0547***	-0.0546***	-0.0021	-0.0042	-0.0037	-0.0079	-0.0436***	-0.0393***
	(0.0066)	(0.0065)	(0.0094)	(0.0093)	(0.0057)	(0.0056)	(0.0121)	(0.0119)
$R0_{i,t} \times$ *Ex/Importer*	0.0075	0.0167*	0.0061	0.0200	0.0039	0.0149*	-0.0014	-0.0045
	(0.0094)	(0.0101)	(0.0134)	(0.0145)	(0.0081)	(0.0088)	(0.0153)	(0.0165)
$R0_{i,t-1} \times$ *Ex/Importer*	0.0176*	0.0243**	-0.0126	0.0005	-0.0078	0.0051	0.0344*	0.0400**
	(0.0099)	(0.0107)	(0.0141)	(0.0152)	(0.0086)	(0.0092)	(0.0181)	(0.0196)
$R0_{i,t-2} \times$ *Ex/Importer*	-0.0164	-0.0217*	-0.0119	0.0117	-0.0096	0.0017	0.0115	-0.0017
	(0.0107)	(0.0115)	(0.0153)	(0.0165)	(0.0093)	(0.0100)	(0.0195)	(0.0210)
$R0_{i,\{t-m,m\geq 3\}} \times$ *Ex/Importer*	-0.0246**	-0.0318***	-0.0145	-0.0047	-0.0375***	-0.0192*	-0.0029	-0.0302
	(0.0108)	(0.0116)	(0.0154)	(0.0166)	(0.0093)	(0.0101)	(0.0203)	(0.0223)
$Ex/Importer_{i,t}$	0.0284***	0.0275***	0.0111***	0.0208***	0.0153***	0.0134***	0.0213***	0.0120***
	(0.0022)	(0.0023)	(0.0031)	(0.0033)	(0.0019)	(0.0020)	(0.0040)	(0.0042)
Observations	1,255,386	1,255,386	1,255,386	1,255,386	1,255,386	1,255,386	808,893	808,893
Number of Panel_id	350,444	350,444	350,444	350,444	350,444	350,444	270,569	270,569
Control for Spillovers (R1-10)	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES
Sector×Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Province×Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Firms of Single Treatment	YES	YES	YES	YES	YES	YES	YES	YES
Firms of Multiple Treatments	NO	NO	NO	NO	NO	NO	NO	NO
Sample Period	2000-09	2000-09	2000-09	2000-09	2000-09	2000-09	2000-07	2000-07

Notes: The table reports the heterogeneous effects between exporters/importers and non-exporters/-importers. $R0_{i,g}$ is equal to 1 if firm i is inundated in year g, thus the coefficients for $R0_{i,t}$, $R0_{i,t-1}$, $R0_{i,t-2}$, and $R0_{i,\{t-m,m\geq 3\}}$ can be interpreted as contemporaneous effect, 1-year lagged effect, 2-year lagged effect, and long-run (3-year onwards) lagged effect of inundation, respectively. $Ex/Importer_{i,t}$ is a dummy equal to 1 if firm i has export/import records in the database of the Chinese Customs Trade Statistics in year t. We explicitly include neighbouring non-inundated firms within 20 kilometres from the inundation areas (R1-10) in all the regressions to control for spillover effects. We use Arellano-Bond method and include firm, sector-year and province-year fixed effects in all the specifications. We can only compute firms' TFP for the period 2000-2007 because of data availability. Standard errors are reported in parentheses under the estimates. Asterisks ***/**/* denote $p < 0.01$, $p < 0.05$, $p < 0.1$, respectively.

Table 8: Inundation Effects on Exports and Imports

	export	import
	(1)	(2)
$R0_{i,t}$	-0.0023	-0.0102
	(0.0257)	(0.0376)
$R0_{i,t-1}$	-0.0009	-0.0687*
	(0.0278)	(0.0406)
$R0_{i,t-2}$	-0.0320	-0.0329
	(0.0296)	(0.0434)
$R0_{i,\{t-m,m\geq 3\}}$	-0.0593*	-0.1430***
	(0.0356)	(0.0526)
$R1\text{-}10_{i,t}$	-0.0058	0.0262
	(0.0104)	(0.0163)
$R1\text{-}10_{i,t-1}$	0.0079	0.0156
	(0.0103)	(0.0161)
$R1\text{-}10_{i,t-2}$	0.0210**	0.0504***
	(0.0097)	(0.0154)
$R1\text{-}10_{i,\{t-m,m\geq 3\}}$	0.0157	-0.0185
	(0.0111)	(0.0176)
Observations	185,156	134,217
Number of Panel_id	56,069	39,317
Firm FE	YES	YES
Sector×Year FE	YES	YES
Province×Year FE	YES	YES
Firms of Single Treatment	YES	YES
Firms of Multiple Treatments	NO	NO
Sample Period	2000-09	2000-09

Notes: The table reports the inundation effects on firms' exports and imports. $R0_{i,g}$ is equal to 1 if firm i is inundated in year g, thus the coefficients for $R0_{i,t}$, $R0_{i,t-1}$, $R0_{i,t-2}$, and $R0_{i,\{t-m,m\geq 3\}}$ can be interpreted as contemporaneous effect, 1-year lagged effect, 2-year lagged effect, and long-run (3-year onwards) lagged effect of inundation, respectively. $R1\text{-}10_{i,g}$ is a dummy equal to 1 if firm i is non-inundated but located within 20 kilometres from the flooding area in year g, and the coefficients for $R1\text{-}10_{i,t}$, $R1\text{-}10_{i,t-1}$, $R1\text{-}10_{i,t-2}$, and $R1\text{-}10_{i,\{t-m,m\geq 3\}}$ represent the corresponding dynamic effects on these neighbouring non-inundated firms. We use Arellano-Bond method and include firm, sector-year and province-year fixed effects in all the specifications. We can only compute firms' TFP for the period 2000-2007 because of data availability. Standard errors are reported in parentheses under the estimates. Asterisks ***/**/* denote $p < 0.01$, $p < 0.05$, $p < 0.1$, respectively.

Table 9: Heterogeneous Effects on Output by Sectors

	Recycle and repair	Automobiles and transport equipments	Paper, printing, and art products	Food, beverages, and tobacco	Machinery	Computers and electronic equipments	Chemical, rubber, and plastics products	Mineral and metal products	Textile, apparel, and foot wear	Wood and furniture	Other manufacture	Gas, electricity, and water	mining
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
$R0_{i,t}$	-0.1104***	-0.0627***	-0.0582***	-0.0572***	-0.0547***	-0.0493***	-0.0468***	-0.0439***	-0.0437***	-0.0278	-0.0582	-0.0273	-0.0159
	(0.0321)	(0.0174)	(0.0170)	(0.0160)	(0.0133)	(0.0158)	(0.0134)	(0.0112)	(0.0122)	(0.0280)	(0.0358)	(0.0184)	(0.0280)
$R0_{i,t-1}$	-0.0867**	-0.0521***	-0.0572***	-0.0670***	-0.0851***	-0.0409**	-0.0706***	-0.0455***	-0.0767***	-0.0528*	-0.0256	-0.0234	-0.0256
	(0.0371)	(0.0200)	(0.0188)	(0.0180)	(0.0150)	(0.0173)	(0.0149)	(0.0125)	(0.0135)	(0.0314)	(0.0433)	(0.0200)	(0.0315)
$R0_{i,t-2}$	-0.0799*	-0.0711***	-0.0976***	-0.0874***	-0.0666***	-0.0506***	-0.0590***	-0.0676***	-0.0991***	-0.0401	-0.0377	-0.0079	-0.0334
	(0.0408)	(0.0215)	(0.0200)	(0.0195)	(0.0159)	(0.0182)	(0.0161)	(0.0135)	(0.0144)	(0.0339)	(0.0462)	(0.0219)	(0.0340)
$R0_{i,\{t-m,m\geq 3\}}$	-0.1679***	-0.0650***	-0.0974***	-0.0755***	-0.0528***	-0.0204	-0.0647***	-0.0342**	-0.0817***	-0.0259	0.0113	-0.0222	-0.0055
	(0.0491)	(0.0248)	(0.0232)	(0.0223)	(0.0182)	(0.0215)	(0.0185)	(0.0157)	(0.0170)	(0.0384)	(0.0571)	(0.0247)	(0.0387)
Observations	27,916	98,111	74,167	109,638	159,809	111,611	140,166	195,655	192,043	37,723	19,024	42,747	46,776
Number of Panel_id	10,015	31,069	20,571	32,520	50,209	33,430	39,947	59,125	54,360	12,690	8,079	9,352	15,818
Control for Spillovers (R1-10)	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Province×Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firms of Single Treatment	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firms of Multiple Treatments	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO
Sample Period	2000-09	2000-09	2000-09	2000-09	2000-09	2000-09	2000-09	2000-09	2000-09	2000-09	2000-09	2000-09	2000-09

Notes: The table reports the inundation effects separately for each sector. The 13 sectors here are merged from the 40 2-digit CIC code sectors according to the similarity. $R0_{i,g}$ is equal to 1 if firm i is inundated in year g, thus the coefficients for $R0_{i,t}$, $R0_{i,t-1}$, $R0_{i,t-2}$, and $R0_{i,\{t-m,m\geq 3\}}$ can be interpreted as contemporaneous effect, 1-year lagged effect, 2-year lagged effect, and long-run (3-year onwards) lagged effect of inundation, respectively. We explicitly include neighbouring non-inundated firms within 20 kilometres from the inundation areas (R1-10) in all the regressions to control for spillover effects. We use Arellano-Bond method and include firm and province-year fixed effects in all the specifications. Standard errors are reported in parentheses under the estimates. Asterisks ***/**/* denote $p < 0.01$, $p < 0.05$, $p < 0.1$, respectively.

Table 10: Inundation Effects on Firm Entry/Exit

	R_{exit}		R_{entry}		ln (#exit)		ln (#entry)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$R0\_bin0_{c,t}$	0.0039	0.0010	-0.0125***	-0.0068	0.0319	0.0066	-0.0023	-0.0018
	(0.0034)	(0.0033)	(0.0046)	(0.0043)	(0.0209)	(0.0181)	(0.0218)	(0.0218)
$R0\_bin0_{c,t-1}$	0.0044	0.0028	-0.0123***	-0.0091**	-0.0049	-0.0187	-0.0434*	-0.0432*
	(0.0036)	(0.0035)	(0.0045)	(0.0041)	(0.0234)	(0.0209)	(0.0237)	(0.0238)
$R0\_bin0_{c,t-2}$	0.0081**	0.0087**	-0.0056	-0.0068	0.0540**	0.0519**	0.0221	0.0220
	(0.0037)	(0.0036)	(0.0045)	(0.0043)	(0.0255)	(0.0230)	(0.0253)	(0.0253)
$R0\_bin0_{c,\{t-m,m\geq3\}}$	-0.0005	-0.0007	-0.0050	-0.0045	0.0276	-0.0003	0.0207	0.0209
	(0.0036)	(0.0037)	(0.0045)	(0.0044)	(0.0243)	(0.0203)	(0.0248)	(0.0249)
$R0\_bin1_{c,t}$	0.0121***	0.0005	-0.0339***	-0.0113*	0.1457***	0.0228	-0.0123	-0.0101
	(0.0046)	(0.0044)	(0.0067)	(0.0060)	(0.0343)	(0.0285)	(0.0345)	(0.0346)
$R0\_bin1_{c,t-1}$	0.0119**	0.0080*	-0.0354***	-0.0278***	0.0531	0.0131	-0.0892**	-0.0891**
	(0.0048)	(0.0047)	(0.0067)	(0.0060)	(0.0355)	(0.0314)	(0.0374)	(0.0374)
$R0\_bin1_{c,t-2}$	0.0180***	0.0199***	-0.0162**	-0.0198***	0.1056***	0.1187***	-0.0619*	-0.0627*
	(0.0048)	(0.0048)	(0.0063)	(0.0060)	(0.0381)	(0.0342)	(0.0375)	(0.0377)
$R0\_bin1_{c,\{t-m,m\geq3\}}$	0.0052	0.0128***	-0.0068	-0.0216***	-0.0155	0.0526*	-0.1481***	-0.1495***
	(0.0039)	(0.0041)	(0.0062)	(0.0058)	(0.0392)	(0.0310)	(0.0399)	(0.0401)
ln (#firms)		0.0791***		-0.1540***		0.9128***		-0.0170
		(0.0034)		(0.0042)		(0.0154)		(0.0178)
Observations	27,155	27,155	27,155	27,155	22,813	22,813	20,666	20,666
R^2	0.5573	0.5783	0.5955	0.6455	0.8042	0.8431	0.8479	0.8479
County FE	YES	YES	YES	YES	YES	YES	YES	YES
Prefecture×Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Sample Period	2000-09	2000-09	2000-09	2000-09	2000-09	2000-09	2000-09	2000-09

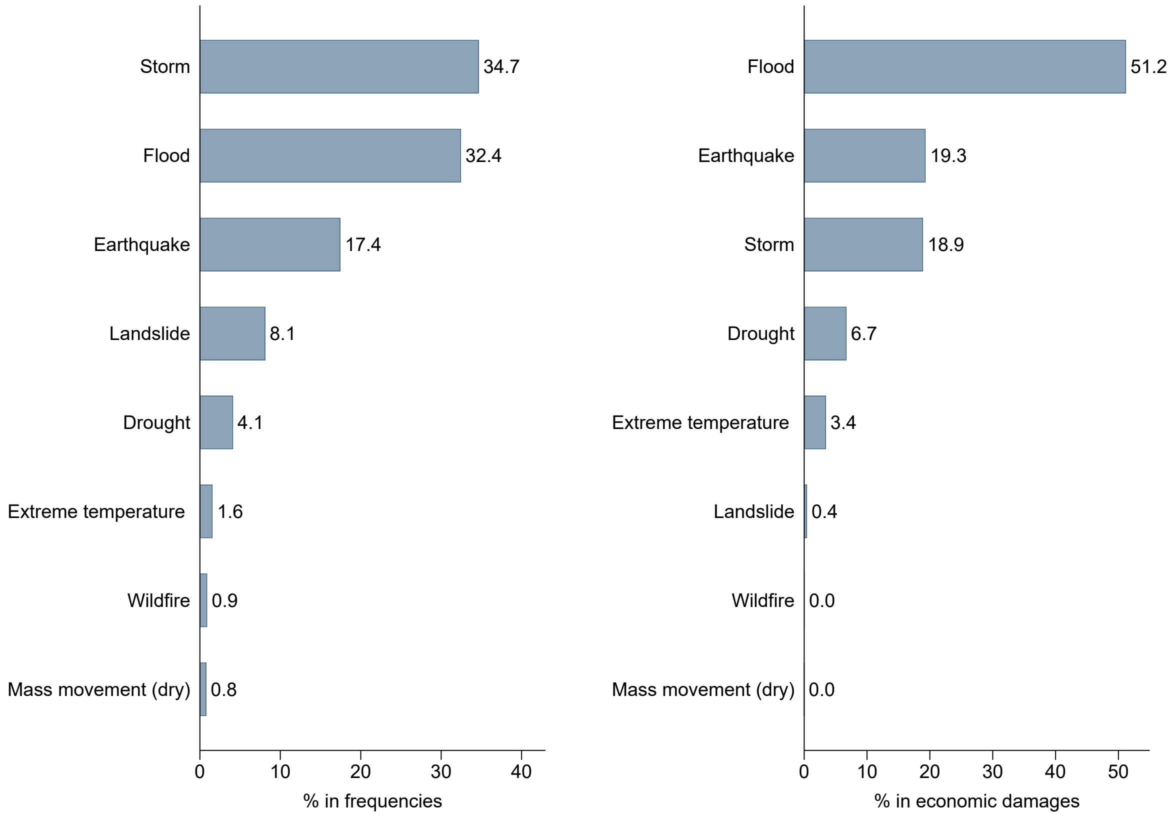
Notes: The table reports the inundation effects on firm entry and exit behaviour in county level. The dependent variables R_{exit}, R_{entry}, ln (#exit), and ln (#entry) are exit rate, entry rate, the number of exit firms (in logarithms), and the number of entrants (in logarithms), respectively. We divide counties into two bins according to the extent that the county is affected by inundation. $R0\_bin0_{c,t}$ is equal to 1 if county c has 1-20 firms that are exposed to inundation in year t. $R0\_bin1_{c,t}$ is equal to 1 if county c has more than 20 firms that are exposed to inundation in year t and 0 otherwise. As in the models for firms, we also investigate the dynamic effects of inundation on counties using the contemporaneous and lagged treatment dummies. We include county, prefecture-year fixed effects in all the specifications. Standard errors are reported in parentheses under the estimates. Asterisks ***/**/* denote $p < 0.01$, $p < 0.05$, $p < 0.1$, respectively.

Table 11: Robustness Checks

	y				k				emp				tfp			
	Baseline	Non-mover	Non-mover & Non-new	Non-mover & Old	Baseline	Non-mover	Non-mover & Non-new	Non-mover & Old	Baseline	Non-mover	Non-mover & Non-new	Non-mover & Old	Baseline	Non-mover	Non-mover & Non-new	Non-mover & Old
$R0_{i,t}$	-0.0548***	-0.0610***	-0.0614***	-0.0747***	-0.0260***	-0.0300**	-0.0267**	-0.0415**	-0.0176***	-0.0221***	-0.0214***	-0.0400***	-0.0562***	-0.0486***	-0.0481***	-0.0285
	(0.0046)	(0.0086)	(0.0086)	(0.0142)	(0.0066)	(0.0121)	(0.0121)	(0.0183)	(0.0040)	(0.0075)	(0.0075)	(0.0112)	(0.0074)	(0.0138)	(0.0138)	(0.0221)
$R0_{i,t-1}$	-0.0657***	-0.0703***	-0.0638***	-0.0948***	-0.0166**	-0.0264**	-0.0014	-0.0564***	-0.0255***	-0.0389***	-0.0297***	-0.0624***	-0.0220**	-0.0032	-0.0156	0.0052
	(0.0051)	(0.0095)	(0.0099)	(0.0166)	(0.0072)	(0.0134)	(0.0139)	(0.0214)	(0.0044)	(0.0083)	(0.0086)	(0.0131)	(0.0090)	(0.0179)	(0.0196)	(0.0293)
$R0_{i,t-2}$	-0.0733***	-0.0842***	-0.0787***	-0.0968***	-0.0173**	-0.0172	-0.0033	-0.0297	-0.0148***	-0.0287***	-0.0178*	-0.0442***	-0.0501***	-0.0466**	-0.0613***	-0.0631*
	(0.0054)	(0.0100)	(0.0108)	(0.0179)	(0.0077)	(0.0141)	(0.0153)	(0.0230)	(0.0047)	(0.0087)	(0.0095)	(0.0141)	(0.0098)	(0.0194)	(0.0227)	(0.0328)
$R0_{i,\{t-m,m\geq 3\}}$	-0.0565***	-0.0569***	-0.0862***	-0.0903***	-0.0055	0.0000	0.0157	-0.0209	-0.0103*	-0.0198*	-0.0126	-0.0402**	-0.0444***	-0.0348	-0.0661**	-0.0592
	(0.0063)	(0.0117)	(0.0142)	(0.0213)	(0.0090)	(0.0165)	(0.0200)	(0.0275)	(0.0054)	(0.0102)	(0.0124)	(0.0168)	(0.0113)	(0.0224)	(0.0275)	(0.0384)
Observations	1,255,386	476,822	465,280	129,359	1,255,386	476,822	465,280	129,359	1,255,386	476,822	465,280	129,359	808,893	269,278	263,709	85,206
Number of Panel_id	350,444	157,210	152,662	42,824	350,444	157,210	152,662	42,824	350,444	157,210	152,662	42,824	270,569	107,921	105,006	33,887
Control for Spillovers (R1-10)	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Sector×Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Province×Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firms of Single Treatment	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firms of Multiple Treatments	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO
Sample Period	2000-09	2000-09	2000-09	2000-09	2000-09	2000-09	2000-09	2000-09	2000-09	2000-09	2000-09	2000-09	2000-07	2000-07	2000-07	2000-07

Notes: The table reports the estimation results when we use different subsamples as robustness checks. For each dependent variable, the first column under "Baseline" is the baseline estimates when we use the whole sample, as the same as the first columns under each dependent variable in Table 3. The second column under "Non-mover" is the estimates when we only include firms that do not change their locations during the sample period. The third column under "Non-mover & Non-new" is the estimates when we further restrict the sample to those who have already existed in the sample for at least two years before their first treatments, conditional on fixed locations ("Non-mover" firms). The last column under "Non-mover & Old" reports the estimates when we use the subsample in which firms do not change their locations during 2000–2009 and with entry ages, defined as the difference between the year that it first appears in the sample and the founding year for each firm, older than 5 years. $R0_{i,g}$ is equal to 1 if firm i is inundated in year g, thus the coefficients for $R0_{i,t}$, $R0_{i,t-1}$, $R0_{i,t-2}$, and $R0_{i,\{t-m,m\geq 3\}}$ can be interpreted as contemporaneous effect, 1-year lagged effect, 2-year lagged effect, and long-run (3-year onwards) lagged effect of inundation, respectively. We explicitly include neighbouring non-inundated firms within 20 kilometres from the inundation areas (R1-10) in all the regressions to control for spillover effects. We use Arellano-Bond method and include firm, sector-year and province-year fixed effects in all the specifications. We can only compute firms' TFP for the period 2000-2007 because of data availability. Standard errors are reported in parentheses under the estimates. Asterisks ***/**/* denote $p < 0.01$, $p < 0.05$, $p < 0.1$, respectively.

Figure 1: Natural Disasters in China during 1970-2021

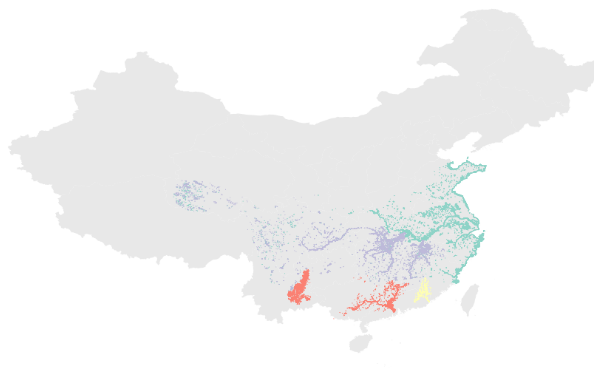


Notes: The figure illustrates the percentage shares of each type of natural disaster in terms of frequency (left panel) and economic damages caused (right panel) among all the disasters that occurred in mainland China from 1970 to 2021.

Figure 2: Inundation Areas and Inundated Firms: GFD vs. DFO in 2002

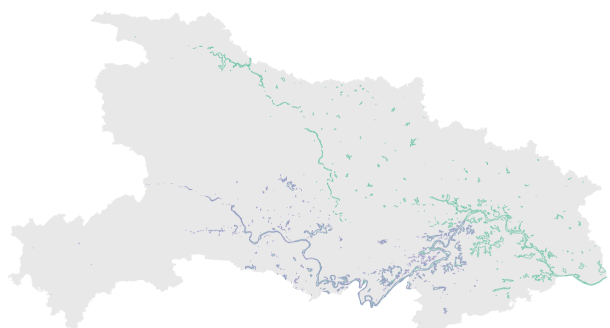
(A) DFO inundation areas in 2002

(B) GFD inundation areas in 2002

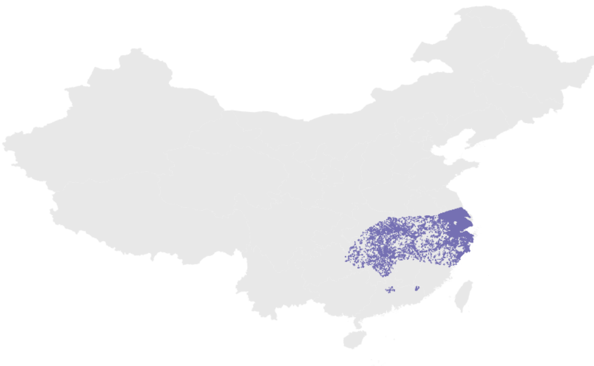


(C) DFO 2002: Zoom in to Hubei province

(D) GFD 2002: Zoom in to Hubei province

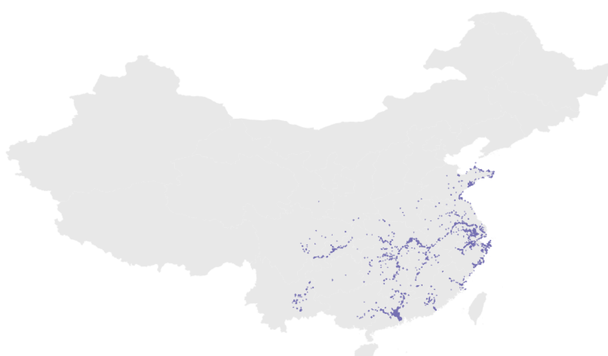


(E) DFO inundated firms in 2002



(F) GFD inundated firms in 2002

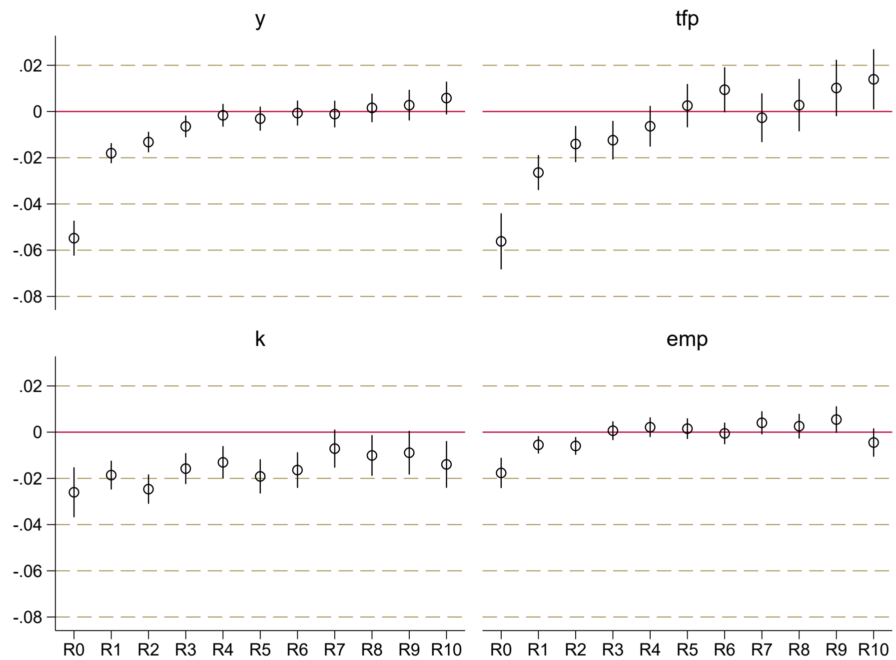
(G) GFD inundated+Adjacent 1km firms in 2002



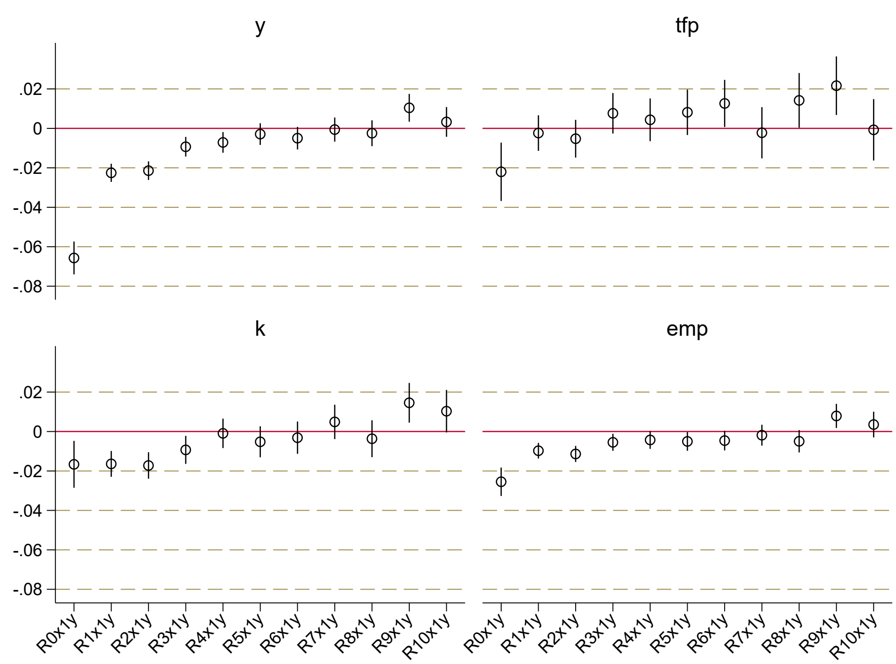
Notes: The figures plot the inundation areas and the corresponding inundated firms on Chinese map for the 4 successfully mapped flood events (from the satellite images) occurred in 2002. Panels (A) and (B) are the inundation areas according to DFO and GFD, respectively. Each color represents one flood event. Panels (C) and (D) show the same inundation polygons when we zoom in to the map of Hubei province for better visualization. Panels (E) and (F) are the inundated firms which are located in the above inundation areas in (A) and (B). Panel (G) illustrates the inundated firms when we expand the inundation areas in GFD (Panel B) outward by 1 kilometer.

Figure 3: Spillover Effects on Neighbouring Non-inundated Firms

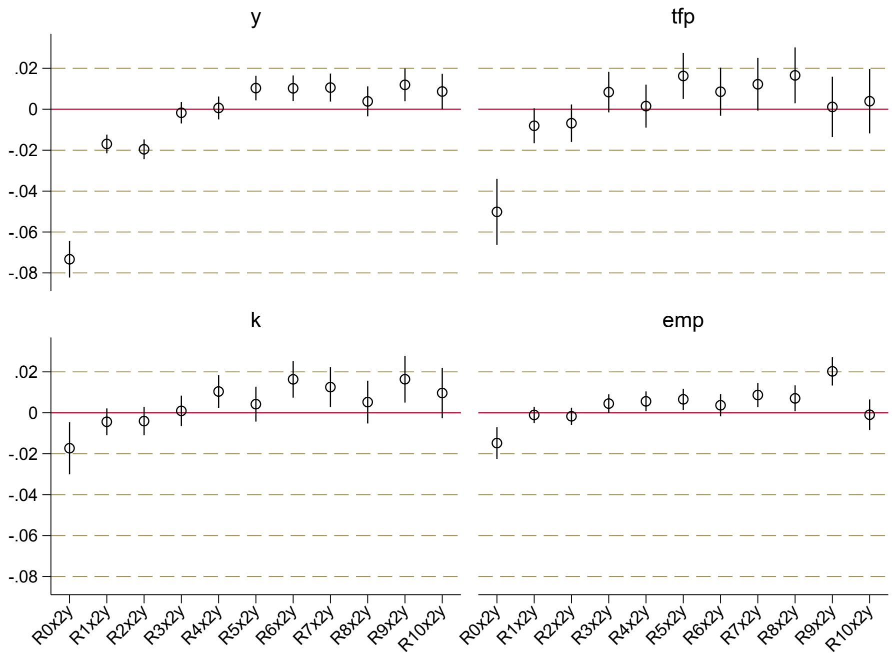
(A) Contemporaneous Effects



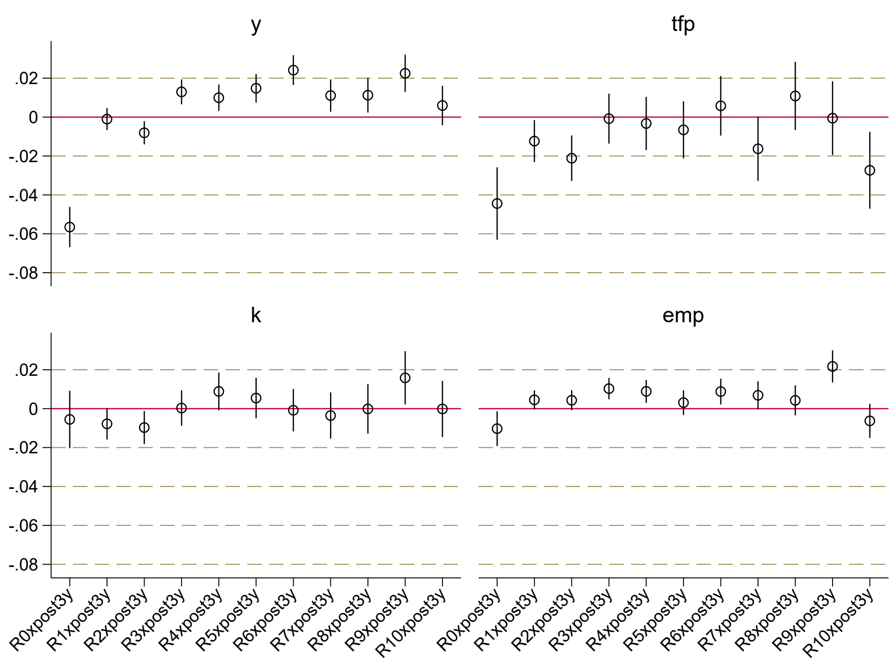
(B) 1-year Lagged Effects



(C) 2-year Lagged Effects



(D) Long-run Effects



Notes: The figure plots the estimates of the flooding effects on inundated firms (denoted as $R0$) and neighbouring non-inundated firms that are located in the ten 2km-width rings surrounding the inundation area (denoted as Rk for firms located in the k-th ring) with their 90 percent confidence intervals, as modelled in Equation (2). Panels (A) – (D) represent the contemporaneous effects, 1-year lagged effects, 2-year lagged effects, and long-run (3-year onwards) lagged effect of the floods, respectively. The sample we use in the estimation excludes firms with multiple treatments.