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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 third year onwards, 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
JEL Classification: C23; D24; Q54

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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 4 and 18 kilometres from the inundated area) expand in their productions (from the third year onwards). The latter positive spillover effects suggest that production activities are reallocated geographically to 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, inventory management practice, 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 (due to, 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 of these studies, while the research subjects are individual households/workers (e.g., Yang and Choi, 2007; Auffhammer and Aroonruengsawat, 2011; Anttila-Hughes and Hsiang, 2013; Somanathan, Somanathan, Sudarshan and Tewari, 2021), plants/firms (e.g., Cachon, Gallino and Olivares, 2012; Graff Zivin and Neidell, 2014; Chen and Yang, 2019; Addoum, Ng and Ortiz-Bobea, 2020; Hossain, 2020), or products (e.g., Jones and Olken, 2010), the treatment groups are usually defined by the administrative geographical unit, such as states, provinces, counties or districts. 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 have to be aggregated to an economically meaningful level that can be matched with the individual entity data for analysis;[3] or the geospatial data on the actual weather/disaster extents are not readily available, so that scholars can only use the affected administrative geographical areas (reported by news or government agencies for floods, typhoons or earthquakes) as proxies for the actual influence scope. Consequently, in both cases, the matching of the weather/disaster data and the economic data is not exact, and the implied allocation of treatment status to individual entities could be prone to large measurement errors (Hsiang, 2016).

In the case of flood, the disaster type of our interest in this paper, the second issue discussed above applies. Specifically, 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 inundation extent and matches it with geocoded firm-level data to allocate the treatment status of a firm, all firms located in the administrative location but outside the small true inundation area would be misclassified as inundated. If the number of misclassified firms makes up a large proportion, the estimation results is potentially severely biased. We will see in the data section that this would be 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. A key innovation of our study is thus 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, alleviating 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

[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) study the impact of temperature on labor in India. The firm-level data they use only document the district where each firm is located and do not contain geographical coordinate information; hence, they aggregate the temperature and rainfall data to the 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 of the aggregation of weather data and a comprehensive review of the climate-economy literature.

two key aspects. First, both of these studies look at a single (year's) major flood event(s) 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 for Chinese firms 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-level 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.

Yet two more closely related work are Hossain (2020) and Hu, Pant, Hall, Surminski and Huang (2019). Hossain (2020) 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 the work, however, is defined at the district rather than the establishment level. 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 being 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 differences in 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 news reports or government announcements and are typically substantially larger than the actual areas of inundation. Second, we use the Annual Surveys of Industrial Firms (ASIF) data of China compiled by the National Bureau of Statistics of China (NBS), which covers all industrial firms with sales above 5 million RMB and is more comprehensive than the Orbis dataset used in their study.

Our study uses a unified specification to estimate the dynamic and spillover effects of floods across time and space. We could first compare our findings with the literature in terms of the former (the dynamic effect), which has been more often studied by literature. Among others, Kocornik-Mina, McDermott, Michaels and Rauch (2020) study how large urban floods affect the economic activities across and within cities on a global scale. 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 use night light data as a 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 inundation (with the length of period depending on the income status of the country where the city is located). In contrast to these studies, we find that the aggregate economic effects at the city level mask considerably differential effects of flood on inundated and non-inundated firms within the city, and that floods have far longer-term or even permanent adverse impacts on the inundated firms.

In relation to spillover effects, Carvalho, Nirei, Saito and Tahbaz-Salehi (2021) study the impact of the Great East Japan Earthquake of 2011 and show that 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 distance from the disaster-area firms. In this paper, we explore the spillover effects based on the geographical distances of firms to the 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, firms that are located further away (but within 18 kilometre radius) from the inundation area enjoy output gain, from the third year onwards after a flood, suggesting 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 takes time to realize.

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

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 include all Chinese state-owned enterprises (SOE), and non-SOE firms with annual sales above 5 million RMB (the "above-scale" firms), in the industrial sectors. 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

Floods cause damage to tangible assets and workers (inputs for production activities) as well as disruptions to the operation (hence efficiency/productivity) of firms. The impacts could extend beyond the current period if it takes time for firms to rebuild the capital stock and labor force, and to restore productivity. As a start, we explore the following preliminary specification, which accommodates potential heterogenous impacts of inundation across time:

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

where Y_{ipst} is a performance measure for firm i located in province p of sector s in year t. In particular, we will evaluate firm-level output (y_{ipst}), total factor productivity (tfp_{ipst}), capital (k_{ipst}), and employment (emp_{ipst}) in logarithm.[9] The treatment status of each firm is indicated by $R0_{i,t-k}$, for $k \in \{0, 1, 2\}$, which equals 1 if firm i was inundated in year $(t-k)$. The coefficient β_k captures the contemporaneous effect for $k = 0$, and the lagged k-year effect for $k \in \{1, 2\}$. The indicator $R0_{i,\{t-m,m\geq 3\}}$ equals 1 if firm i was ever inundated

[9] Note that all the nominal variables in value, such as output and capital stock, are deflated to the 1998 national price level in China, as documented in Section 2.

in periods $(t - m)$ for $m \geq 3$; the coefficient β_3 therefore represents the long-run (3-year onwards) average effect of floods on inundated firms.

We also include control variables that could affect a performance measure of the firm, including its total asset, asset structure (Leiter, Oberhofer and Raschky, 2009), and other performance measures. These controls, however, could be directly affected by the inundation status of the firm or by confounders that simultaneously interact with all performance measures. Hence, we use the lagged one-period values of these controls to reduce the endogeneity concern. Specifically, $X_{i,t-1}$ includes lagged one-period total asset $asset_{i,t-1}$, share of current asset $sca_{i,t-1}$, output $y_{i,t-1}$ (or productivity $tfp_{i,t-1}$ alternately conditional on the performance measure under study), capital $k_{i,t-1}$, and employment $emp_{i,t-1}$, in addition to the firm's age $age_{i,t}$. A 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 are in logarithms.

We also include a list of fixed effects to control for potential observed/unobserved confounders. For example, floods (especially river floods) usually have strong spatial patterns. Firms located in regions near the main waterways are more prone to floods. To account for these location heterogeneities across firms (that could influence the probabilities of treatment) as well as other time-invariant characteristics of firms, we include individual firm fixed effects, δ_i, in the list of controls. We further include sector-time fixed effects to control for sector-year specific shocks (e.g., due to structural changes across sectors during the sample period), and province-year fixed effects to control for policy shocks or other weather/disaster events (e.g., temperature and rainfall) specific to the province-year. We use the dynamic panel estimator of Arellano and Bond (1991) to estimate the specification in Equation (1), and the other specifications below, with the panel unit at the firm level.

In the data, some firms might be subject to floods in multiple years. For example, it may be flooded in the current period, so that $R0_{i,t} = 1$, but it may also be flooded in the previous year, so that $R0_{i,t-1} = 1$. With various trajectories of treatment history for these multiple-treated firms, it is challenging if not impossible to disentangle the contemporaneous effects of inundation from the lagged effects. Thus, for the main analyses, we focus on single-treated firms (firms that were flooded only in one year in the period studied) and estimate the effects of inundation relative to untreated firm-year observations. In Section 4, we address the potential issue of firms being subject to earlier treatments prior to the period studied and demonstrate the robustness of the main findings to such concerns.

Table 2 reports the estimation results based on Equation (1) and its variations. For each performance measure, we experiment with four dynamic specifications. The first specification includes $R0_{i,t}$ only, and thus assumes away lagged effects of floods. The second specification assumes the flood to have permanent effects post treatment, akin to the conventional *DID* specification. The third specifications allows the contemporaneous effect to differ from the average lagged effect, while the fourth specification corresponds to Equation (1), which further allows the lagged effects to differ across one, two, and subsequent years post treatment. Comparison of the results across the four specifications suggests that the negative effects of inundation persist and are not homogeneous across periods post treatment. We hence adopt the more general dynamic specification in Equation (1) as the baseline for the subsequent analyses.

The preliminary results based on Equation (1) suggest that the effects of inundation on corporate output, productivity, capital and labor inputs are all negative and extend beyond the period of treatment. The reductions in output, labor input and productivity are in fact permanent, while capital input could be restored to pre-disaster levels after two years. For output and productivity, the negative effects peak in the second year post treatment (4.8 percent versus 7.2 percent in the current and the second year post treatment for output; and 4.5 percent versus 5.2 percent for productivity). The average lagged effects from the third year onwards are at 6.2% and 4.3% for output and productivity, respectively. This suggests that being inundated once could permanently reduce a firm's production activity/capacity. This is in stark contrast with the findings of Kocornik-Mina et al. (2020) and Gandhi et al. (2022), as discussed in Section 1.1, who suggest that economic activities at the city level (based on night lights as a proxy) typically recover within a year (or 1 to 2 months' time) after the inundation.

3.1 Spillover Effects

We now generalize the specification in Equation (1) to take into account the spillover effects of flood events on non-inundated firms. Such spillovers may take place, for example, due to destruction of the local transportation network, which the neighbouring non-inundated firms may depend upon to various extents (conditional on alternative routes available). The negative spillover effect may also transmit via the local input-output linkages if the regional production network is dense. On the other hand, the spillover effect could also be manifested in reallocation of market shares and sourcing strategies. For example, the downstream firms that used to purchase intermediate inputs from the inundated firms might divert their sourcing to non-inundated suppliers in the area if feasible (to reduce disruptions to their own operations). This leads to a potential positive spillover effect on the untreated neighboring firms.

To evaluate these potential geographic spillover effects, we measure the distance of each firm to the inundation areas and conduct concentric ring analysis. Specifically, we adopt 2 kilometers as the bandwidth of a ring and classify the neighborhood of a firm by the ring it is located in relative to the inundation area. The specification is generalized to include these ring indicators as follows:

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

where $R0_{i,t}$ is defined the same as previously, and $Rk_{i,t}$ for $k > 0$ is a dummy indicating whether firm i is located in the k-th ring (i.e., with a distance between $2(k-1)$ and $2k$ kilometers) away from an inundation area in year t. This geographic spillover specification is embedded in the dynamic specification of Equation (1), such that for each contemporary and post-treatment period (lagged 1-year, 2-year, and 3-year onwards), a set of ground-zero and 10-ring neighborhood effects are estimated. The list of additional controls and fixed effects remain the same as in Equation (1).

Table 3 reports the inundation effects based on Equation (2), in comparison with the preliminary results based on Equation (1). The effects on inundated firms (in particular, the contemporaneous effects) tend to be larger in magnitude when the spillover effects are controlled for, although the differences are not statistically significant.

Figure 3 plots the effects of floods across rings and time. Panel (A) illustrates the pattern of spillover effects for the year of inundation. All the inundated firms and non-inundated firms within 12 kilometres from the inundation area reduce their capital inputs in the immediate year of floods. In contrast, the negative impacts on output and productivity are limited to those located within 6 kilometres, and the negative spillover effects are much smaller in magnitude than the direct effects on inundated firms and decrease with distance. The negative spillover effects on employment are furthermore limited in scope (4 kilometres) and in magnitude.

Panel (B) reports the spillover effects one year post the flood. The negative spillover effects on output and employment tend to worsen in magnitude, although the geographic scope of spillover is similar one year post the flood compared to the year of flood. In contrast, firms in all rings of neighborhood recover their productivity one year post the flood, while firms outside the third ring restore their capital inputs one year post the flood. Panels (C) and (D) report the lagged 2-year and longer-run effects. Two years after the flood, while firms located in the first two rings of neighborhood still sustain output losses, firms located further away restore their normality in terms of outputs (ring 3 and ring 4) or even start to outperform their counterparts in terms of outputs (rings 5–9) by around 2%. The positive spillover effects on outputs of firms located in these neighborhoods are driven mostly by increases in capital inputs and productivity, and less due to increases in employment. In longer run, the spillover effects are not regular and cannot be precisely estimated for capital inputs and productivity. There tend to be persistent positive spillover effects in terms of outputs (and to a smaller extent in employment).

To sum up, the inundation effects spill over to non-inundated firms in the neighborhoods that are not directly exposed to the flood. More importantly, the spillover effects on firms in the neighborhoods are differential, depending on their distances from the inundation area. Firms located close to the inundation area (within 4km) are also negatively affected, although the effects sustained are much smaller in magnitude than those sustained by inundated firms (2% vs. 6% in outputs) and tend to dissipate in the long run. Firms that are further away (located between 4–18km from the inundation area) start to experience positive spillover effects in outputs from the third year onwards. These positive spillover effects are in contrast with the long-run shrinkage of the inundated firms. In the short run, inundated firms are mainly subject to the direct flood 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 such that their long-run outputs are below the pre-disaster level.

It is also worthwhile to note that when we include the firms in the neighborhoods in the concentric ring specification (and hence label them as geographically treated firms and not as among the control group), the estimated effects of inundation for the directly treated firms tend to be larger in magnitude for the current year and one year after the flood, relative to the preliminary results based on Equation (1), as seen in Table 3. This is a reinforcing evidence of spillover effects. As such, in the estimations below, we adopt Equation (2) as our baseline specification and explicitly control for potential spillover effects on firms in the neighborhoods within 20 kilometres (R1-10) of inundation areas.

3.2 Moderating Factors

Given the average baseline effects identified above, we now explore factors that could moderate or aggravate the impacts of inundation. We consider potential heterogeneous effects due to firm asset structures, inventory management, ownership types, geographical locations, export/import status, and industrial sectors. These firm-level characteristics are obtained from the ASIF and CCTS databases as documented in Section 2. All these analyses are conducted expanding on the baseline specification of Equation (2).

3.2.1 Asset Structures

A firm's asset structure could affect how vulnerable it is to floods. Tangible assets (defined as the sum of fixed assets and inventory) are potentially more exposed to physical destruction. Firms with a larger share of tangible assets thus may sustain larger negative impacts from floods and also take longer time to recover. We test this hypothesis by adding an interaction term of each treatment dummy with an asset tangibility indicator, $Tangibility_i$. In particular, we define firm i to be intensive in tangible assets in year t if its share of tangible assets is above the 90 percentile of all firms in year t. The indicator, $Tangibility_i$, is set equal to 1 if firm i is tangible-asset-intensive in at least 50 percent of the time when the firm is observed in the sample. For example, if firm i is observed in 6 years during the period of our study, $Tangibility_i$ is equal to 1 if the firm is tangible-asset-intensive in at least 3 years (and 0 otherwise).

Table 4 reports the estimation results. We find that the coefficients of the interaction terms for output, capital and productivity are mostly negative. This implies that firms intensive in tangible assets suffer more losses in capital (additional 3–12 percent) and also in productivity, which in turn aggravate the negative impacts on their outputs relative to firms less intensive in tangible assets. The additional losses in productivity and output of these firms tend not to be permanent. In contrast, these firms suffer long-run reduction in the scale of capital inputs and do not restore it to the pre-disaster level (as their counterparts would do).

3.2.2 Inventory Management

Natural disasters are usually low-probability but high-impact events for individual firms, and could cause supply chain disruptions (Carvalho, Nirei, Saito and Tahbaz-Salehi, 2021). Inventory management can serve as a safety mechanism to build flexibility and resilience to supply chain disruptions and to mitigate the effects of disaster shocks. Keeping excess inventory stocks provides a buffer in the event of supply chain or production disruptions, although this needs to be balanced against the advantage of just-in-time procurement and lean production (Gunessee, Subramanian and Ning, 2018). In this section, we analyze whether a firm's inventory management policy affects its performances when and after being flooded.

We use *inventory turnover*, a financial metric defined as the ratio of cost of goods sold to inventory of a firm in a year, to measure how lean a firm's inventory stock is (relative to its size). Hence, a relatively low inventory turnover corresponds to relatively more excess inventories, while a higher ratio indicates relatively lean inventory stocks.

A firm is classified as having relatively more excess inventories in a year if its inventory turnover is below the industry median in the year.[10] The firm-specific indicator, $SafeInv_i$, is set equal to 1 if (1) firm i has relatively more excess inventories in the year prior to the treatment year, provided that it is inundated; or (2) firm i has relatively more excess inventories in at least one year, provided that it is never inundated (during the period studied). We then divide the sample into two subsamples based on this dummy $SafeInv_i$. In other words, we dichotomize the firms based on whether they tend to hold excess inventory stocks or not, and examine the role of excess inventory in moderating the inundation effects (by comparing the inundation effects between the two groups). The way we define $SafeInv_i$ also takes care of the potential endogeneity concern that a firm may change its inventory strategy after being hit by a flood.

The results are reported in Table 5. We find that firms with relatively higher inventory stocks (prior to the inundation) can better buffer the negative consequences of floods in output and productivity, but they are subject to much more severe and longer-term damages in terms of physical assets. Their productivity is negatively affected only in the immediate year and their output levels tend to recover from the third year onwards post the floods. In contrast, firms practising lean inventory management sustain losses in outputs and productivity (of more than 10%) due to the floods, and the effects persist in the long run. Employment losses are permanent in both cases, although the inundation effects tend to be milder for firms with relatively higher inventory stocks.

3.2.3 Ownership Types

It might be interesting to know whether state-owned enterprises (SOEs) in China react differently to floods in comparison with private firms. On one hand, since SOEs could have better access to external financial resources, they might be better able to remedy/contain the direct impacts of floods (Pan and Qiu, 2022). Post floods, they might also be charged with social stability objectives (Bai, Lu and Tao, 2006), and required to maintain employment targets (instead of scaling down production activities if need be). On the other hand, SOEs in China generally are more intensive in tangible assets, and hence could be more negatively affected by floods given our arguments in Section 3.2.1.

We classify a firm's ownership type based on its entry in ASIF, and define the SOE indicator, $SOE_{i,t}$, at the firm-year level. The indicator is not time-invariant, as it is possible for a firm to change its ownership type during the sample period. In particular, China went through a trend of privatization after its accession in 2001 to WTO (Chen, Igami, Sawada and Xiao, 2021). Of all the 634,131 firms in our sample, 56,119 (8.8%) were registered as SOEs for at least one year during the period of study (2000–2009). Of this SOE group, 14,524

[10] Industry is defined at the 4-digit GB/T level, finer than the 2-digit sector definition.

(25.9%) firms changed their ownership type.[11] We append the specification of Equation (2) with the interaction terms of the treatment dummies and the SOE indicator.

Table 6 summarizes the results. Consistent with the literature, the coefficient estimate for the level indicator, $SOE_{i,t}$, suggests that SOEs are generally larger in terms of capital stocks and employment size, but less productive and produce less output (conditional on inputs), relative to non-SOEs. In addition, the coefficient estimates for the interaction terms are mostly negative and exhibit patterns similar to those seen in Table 4 on asset tangibility. This suggests that the mechanism of asset tangibility dominates in SOEs' responses to floods. Nonetheless, the differential effect of floods on SOEs in terms of output tends to be larger in magnitude than their counterparts in Table 4, and the negative additional impacts persist in the long run. On the other hand, the differential effect of floods on SOEs in terms of capital inputs tends to be milder than their counterparts in Table 4. Together, this suggests that additional state support and resources that SOEs could potentially fall back on help cushion the negative impacts of floods on their capital inputs, but SOEs' productivity and outputs suffer bigger losses, beyond the excess damage due to asset tangibility, highlighting the inefficiencies of SOEs in production and weaker incentives to recover in the aftermath of floods relative to non-SOEs.

3.2.4 Geographical Locations

Given the locations of the waterways and water bodies, different areas are subject to flood risks at various degrees. Local governments in flood-prone areas often invest heavier in flood control/containment facilities to reduce the severity of the flood impacts. Firms may also take more precautionary/adaptive measures if they know they are subject to higher flood risks. Hence, we might expect firms located in flood-prone areas to perform differently if inundated, in comparison with firms located in less flood-prone areas but hit by floods.

Toward this, we define a county as flood prone and set $ProneCounty_c$ to 1 if county c was hit by floods for more than 5 times during 2000–2014.[12] We then append the baseline specification in Equation (2) with interaction terms of the treatment dummies $R0$ and $ProneCounty_c$. Recall that the treated observations include only single-treated firms; we have excluded from the sample firms that are subject to floods in multiple years (whether

[11] In particular, of the 56,119 SOEs, 12,444 (22.2%) firms changed from SOEs to non-SOEs, 5,005 (8.9%) firms changed from non-SOEs to SOEs. A total of 2,925 SOE firms changed their ownerships more than once. If we exclude these firms, 9,519 firms changed from SOEs to non-SOE, and 2,080 firms changed from non-SOEs to SOEs (i.e., 14,524 = 9,519 + 2,080 + 2,925).

[12] As shown in Figure 2, the areas of inundation are small, fragmented and spanning across provinces. A county is identified as flooded in a flood event if parts of it are inundated by the flood event. During 2000–2014, 785 counties were inundated at least once, among which 36 counties (5%) encountered more than 5 floods. The maximum number of floods a county experienced during the period is 11.

they are located in flood-prone counties or not) to avoid confounding mechanisms and interpretations.

As shown in Table 7, all of the coefficient estimates of the interaction terms are positive and most of them are significant. Thus firms located in flood-prone counties are considerably less affected by floods. In contrast with the permanent reduction in output activities of inundated firms located in less flood-prone counties, firms located in counties of higher flood risks do not sustain long-run negative effects. This result also indicates that the baseline estimates in Table 3 mask important heterogeneity across firms in terms of preparedness to floods.

3.2.5 Export/Import Status

Given the importance of trade to the Chinese economy, we examine whether floods might affect firms of different trade status differentially. A firm-year observation in ASIF is identified as engaged in export/import activities if the firm in the year has export/import records in the CCTS database. We include the interaction terms of the treatment dummies and the exporter/importer indicator ($Exporter_{i,t}/Importer_{i,t}$) to estimate the differential inundation effects on exporters/importers.[13]

The results are reported in Table 8. The coefficient estimates of $Exporter_{i,t}/Importer_{i,t}$ indicate that exporters/importers generally are more productive, and larger in terms of capital stocks, employment size and outputs, in line with the literature à la Melitz (2003). The impacts of floods on exporter/importers is not regular in the initial years after the floods, but in the long run, exporters/importers reduce their scales by more in terms of output and employment size relative to inundated non-exporters/non-importers. The long-run losses of inundated exporters/importers is consistent with the pattern in the baseline results: The market share of inundated exporters/importers flows to neighbouring non-inundated firms in the long haul, but the magnitudes of losses are larger than observed of inundated domestic firms. For inundated exporters, they not only lose market shares in the domestic market, but also in the international market. This is supported by the results in Table 9, where we examine the inundation effects on the exports and imports of the firms. It shows that the inundated firms' exports tend to decrease in the long run, while neighboring non-inundated firms' exports increase but only in the short run. This suggests that overall, the Chinese firms' exports decrease due to floods. In Tables 8–9, the effects on import activities tend to

[13] There are 437,650 exporter-year observations and 328,627 importer-year observations in the sample. A total of 269,003 observations have both indicators equal to one. If we define a firm as an exporter if it has ever been an exporter for at least one year during the period studied, there are 130,321 exporters. Similarly defined, there are 102,350 importers in the sample. A total of 81,373 firms are both exporters and importers.

mirror those on the export activities, suggesting a strong correlation of the two activities at the firm level.

3.2.6 Industrial Sectors

We now examine potential heterogeneous effects of inundation across sectors, whose natures of production might determine their vulnerability to flood risks. Toward this, we group the original 40 sectors (at 2-digit GB/T level) into 13 broad sectors, with industries within each broad sector likely sharing similar production structures. We run the baseline regression in Equation (2) sector by sector (dropping the original sector-year fixed effect controls). The results are reported in Table 10, with the sectors ranked in descending orders of the immediate inundation impacts across columns.

For the majority of sectors, inundated firms suffer long-lasting negative impacts in terms of outputs. The sectors that sustain stronger negative impacts from floods tend to be those that are capital intensive (e.g., recycle and repair, automobiles/transport equipments, and machinery), or produce products that are sensitive to humidity and sanitary conditions (such as paper/printing, and food products). In contrast, the sector of computers/electronics does not exhibit systematic long-run reduction in outputs post the flood, and a few sectors (which includes wood, utilities, and mining) are less vulnerable to inundation.

3.3 Effects on Firm Entry/Exit

In the above analyses, we have examined the effects of floods on the intensive margins of firm performances. We now investigate the effects of floods on the extensive margins of firm dynamics, in terms of firm entry and exit rates at the county level. Gandhi, Kahn, Kochhar, Lall and Tandel (2022) find that population growth is slower in cities that experience more frequent flood events. In similar spirits, floods may also affect the locational choice of potential firm entrants and/or induce exits of firms negatively affected by floods.

We first link each firm across years for the period 1998–2013. The entry and exit years of a firm are defined as the first and last year it exists in the sample.[14] We assume that a firm is operating throughout the years in between (even when a firm-year observation is missing in between the entry and exit years). We then calculate the number of firm entrants and exits at the county-year level, and estimate the impact of flood events on the firm entry and

[14]Given the use of ASIF dataset, the entry and exit are defined as entry into and exit from the ASIF database. These are limited to the "above-scale" firms, i.e., all SOEs and non-SOEs with annual sales above 5 million RMB, as documented in Section 2.

exit for the period 2000–2009. In particular, we estimate the following specification:

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

where the dependent variable is the exit/entry rate (or the logarithm of the number of exit/entry firms) of county c in prefecture r in year t. We classify flooded counties into bin 0 (where 1–20 firms are inundated in county c in year t) and bin 1 (where more than 20 firms are inundated in county c in year t). In particular, the indicator $R0\_bin0_{c,t}$ is set equal to 1 if up to 20 firms are inundated in county c in year t. In parallel, the indicator $R0\_bin1_{c,t}$ equals 1 if more than 20 firms are inundated in county c in year t. As in the baseline, we allow for the lagged 1-year, lagged 2-year, and long-run effects of floods on the entry/exit behaviour of the treated counties. The county fixed effects δ_c are included to control for any time-invariant county characteristics, and the prefecture-time fixed effects δ_{rt} to control for higher administrative-level shocks that are common to the counties in a prefecture-year.

The results are reported in Table 11. We find that the exit rate of firms in a county increases in the second year after the county is hit by a flood, and the entry rate of firms decreases in the short run for the immediate year and the first year post the flood. In addition, the coefficient estimates for bin 1 counties are larger in magnitude than those for bin 0 counties. The exit effects are felt throughout the immediate year to the second year post the flood, while the entry effects last till the second year post the flood. This suggests that the magnitudes of the impact increase with the severity of the inundation in a county. The patterns are similar if we look at the exit and entry in terms of the absolute number of firms. This is partially due to the fact that the county fixed effects included have helped control for the average number of firms in a county. The results are robust and similar if we further include the number of firms in a county-year as an additional control. However, with this more comprehensive set of controls, we find that floods now have permanent effects on the exit rate (and the number of exit firms) and the entry rate as well, beyond the short-run effects documented above.

4 Robustness Checks

We next conduct robustness checks to address potential threats to identification of the inundation effects obtained based on the benchmark specification proposed in Equation (2).

As suggested by the analysis in Section 3.3, firms may enter and exit from a location across time. The endogenous choice of locations by firms could lead to sample selection bias. To reduce the concern about this potential confounding effect, in the first robustness check, we restrict the set of firms to those that remain in the same location ("non-mover") during the sample period 2000–2009. In particular, we round up firms' coordinates (latitudes and longitudes) to 2 decimal places (which permits an error of 1.11 kilometres) and define a firm as a "non-mover" if its coordinates are the same across years. Table 12 reports the results given the restricted sample. In comparison with the baseline estimates (in the first column, repeated from Table 3), the pattern of inundation effects remains similar: firms hit by a flood suffer perpetual losses in outputs and employment size, and operate in a smaller scale in the aftermath of the flood. The magnitudes of the effects on outputs and employment size also tend to be larger than the baseline, although the differences are not statistically significant. For capital and productivity, the effects tend to be shorter-lived and less persistent based on the "non-mover" sample relative to the baseline.

In the next robustness checks, we further restrict the sample to firms that remain in the same location and are not hit by a flood until being in a location for at least two years ("non-mover & non-new"). This is to circumvent the potential concern that a firm might have moved to the current location after being inundated somewhere else before the sample period. These firms with recent inundation experiences may behave and perform differently from the firms that have operated in a fixed location for years before being hit by floods (and are not forced to liquidate or exit the market after the flood). Alternatively, in the other robustness check, we restrict the sample to firms that remain in the same locations and have an entry age older than 5 years ("non-mover & old"), where the entry age is defined as the difference between the year it first appears in the sample and its registered founding year. This excludes the newly incorporated firms or new entrants, who may have fundamentally different production/governance structures from the established/survival firms. Table 12 suggests that the negative impacts on outputs of inundated firms tend to strengthen with the further restricted samples and continue to be persistent. The negative impacts on capital stocks continue to be observed only in the short run. Depending on which sample we focus on, the negative impacts on employment size based on "non-mover & old" strengthens relative to those based on "non-mover & non-new". On the other hand, the negative impacts on productivity are more pronounced for the "non-mover & non-new" sample than those for the "non-mover & old" sample. Overall, these exercises suggest that our baseline findings of dynamic inundation effects are robust to potential firm relocations.

5 Conclusion

A key challenge in identifying the causal effects of floods on individual firms is to measure the actual incidence of floods at the firm level, which requires matching the inundation area and firm location in high spatial resolution. The inundation extent of a flood event can only be precisely measured from remote sensing instruments, while firms' operating addresses have to be geographically codable/coded, so that the latter can be mapped with the identified inundation areas. This article is among the first in the literature to identify the flood exposure directly at the disaggregated firm level, by merging the satellite-observed inundation areas with the GPS geocoded firm locations. We use this novel dataset to study the impacts of floods on firm performance measures in China during the period 2000–2009.

We find that on average, a firm is subject to long-run reduction in production capacity and productivity (by 6% and 5%, respectively) if hit by floods. The effects also spill over to firms in the neighborhoods that are not directly exposed to floods, but differently depending on their distances to the inundation area. Firms that are in close proximity (within 4 kilometres) to the inundation area are negatively affected as the inundated firms, but at a much smaller magnitude, and could resume pre-disaster production level in three years. Firms that are located further away (between 4 and 18 kilometres) from the inundation area are not significantly affected in the first two years and increase their production scales thereafter. This suggests that in addition to the direct impacts of floods in the short run, the inundated firms are further subject to the negative effects in the long run, as market shares reallocate toward non-inundated firms in the surrounding neighborhoods.

We also investigate factors that could moderate or aggravate the negative impacts of inundation, including firm asset structures, inventory management practices, ownership types, geographical locations, export/import status, and industrial sectors. Firms that are tangible-asset intensive, with relatively lean inventory stocks, and state owned are found to be more negatively affected by floods. On the other hand, firms located in flood-prone counties fare better and sustain losses that are relatively minor and temporary, which suggests better preparedness and adaptation by local governments and firms in counties anticipating higher flood hazards. In addition to the intensive margin, we also investigate the effects of floods on the extensive margin. By aggregating the firm-level data to the county level, we find that the exit rate in severely flooded counties is higher by 1.2–1.8 percent (while the entry rate is lower by 1.6–3.5 percent) in the immediate and following two 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 economic activities to pre-disaster levels within a year. Our study, however, finds that inundated firms in non-flood-prone areas are subject to permanent reduction in productivity and outputs. 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 heterogeneous impacts.

Lastly, we note that the estimates we have obtained could be considered conservative, in the sense that the GFD only successfully maps one third of all the flood events that took place during the period studied, and hence some inundated firms may have been misclassified as among the control group, causing potential attenuation bias as a result. Meanwhile, because the firm-level data are available only at the annual frequency, we have aggregated flood events within a year[15] and used simply binary variables to indicate flood exposures. These prevent us from identifying the impacts of floods according to the intensity of the floods. We leave these further refinements in measurement of flood intensity to future research.

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[15] The aggregation of flood events in a year is by taking the union of the inundation areas within a year. The distances between firms and the inundation area in a year are calculated based on the aggregated inundation area so that they are well defined.

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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	NO	YES	NO	YES	NO	YES	NO	YES
$R0_{i,t}$	-0.0476***	-0.0548***	-0.0122**	-0.0260***	-0.0158***	-0.0176***	-0.0454***	-0.0562***
	(0.0043)	(0.0046)	(0.0062)	(0.0066)	(0.0037)	(0.0040)	(0.0068)	(0.0074)
$R0_{i,t-1}$	-0.0572***	-0.0657***	-0.0110	-0.0166**	-0.0199***	-0.0255***	-0.0257***	-0.0220**
	(0.0048)	(0.0051)	(0.0069)	(0.0072)	(0.0042)	(0.0044)	(0.0086)	(0.0090)
$R0_{i,t-2}$	-0.0721***	-0.0733***	-0.0214***	-0.0173**	-0.0175***	-0.0148***	-0.0518***	-0.0501***
	(0.0053)	(0.0054)	(0.0076)	(0.0077)	(0.0046)	(0.0047)	(0.0096)	(0.0098)
$R0_{i,\{t-m,m\geq 3\}}$	-0.0621***	-0.0565***	-0.0069	-0.0055	-0.0136**	-0.0103*	-0.0428***	-0.0444***
	(0.0063)	(0.0063)	(0.0089)	(0.0090)	(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)
$R0_{i,\{t-m,m\geq 3\}}$	-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)
$R0_{i,\{t-m,m\geq 3\}} \times Tangibility_i$	-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 $R0_{i,\{t-m,m\geq 3\}}$ 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. $Tangibility_i$ 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 Safety Inventory Stocks

	y		k		emp		tfp	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
With Excess Inventory	NO	YES	NO	YES	NO	YES	NO	YES
$R0_{i,t}$	-0.0882***	-0.0317***	-0.0308***	-0.0390***	-0.0261***	-0.0188***	-0.0641***	-0.0346***
	(0.0064)	(0.0063)	(0.0107)	(0.0086)	(0.0062)	(0.0053)	(0.0106)	(0.0102)
$R0_{i,t-1}$	-0.1230***	-0.0303***	-0.0069	-0.0513***	-0.0354***	-0.0346***	-0.0732***	0.0200
	(0.0071)	(0.0070)	(0.0119)	(0.0096)	(0.0069)	(0.0059)	(0.0129)	(0.0127)
$R0_{i,t-2}$	-0.1554***	-0.0367***	-0.0111	-0.0531***	-0.0225***	-0.0300***	-0.1342***	0.0044
	(0.0075)	(0.0075)	(0.0126)	(0.0102)	(0.0073)	(0.0063)	(0.0138)	(0.0139)
$R0_{i,\{t-m,m\geq 3\}}$	-0.1591***	-0.0119	-0.0136	-0.0527***	-0.0394***	-0.0220***	-0.1635***	0.0263
	(0.0087)	(0.0086)	(0.0145)	(0.0117)	(0.0084)	(0.0072)	(0.0157)	(0.0160)
Observations	311,943	956,195	311,943	956,195	311,943	956,195	196,402	619,069
Number of Panel_id	101,784	253,190	101,784	253,190	101,784	253,190	73,797	199,822
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 compares the dynamic inundation effects between firms with and without excess inventory. The definition for excess inventory is as the text in Section 3.2.2. $R0_{i,g}$ 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.

Table 6: 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)
$R0_{i,\{t-m,m\geq3\}}$	-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)
$R0_{i,\{t-m,m\geq3\}} \times SOE$	-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 $R0_{i,\{t-m,m\geq3\}}$ 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. $SOE_{i,t}$ 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 7: 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)
$R0_{i,\{t-m,m\geq3\}}$	-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)
$R0_{i,\{t-m,m\geq3\}} \times ProneCounty_c$	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 $R0_{i,\{t-m,m\geq3\}}$ 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. $ProneCounty_c$ 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 8: 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)
$R0_{i,t} \times Ex/Importer_{i,t}$	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)
$R0_{i,t-1} \times Ex/Importer_{i,t}$	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)
$R0_{i,t-2} \times Ex/Importer_{i,t}$	-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)
$R0_{i,\{t-m,m\geq 3\}} \times Ex/Importer_{i,t}$	-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 9: 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 10: 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. We group the original 40 sectors (at 2-digit GB/T level) into 13 broad sectors, with industries within each broad sector likely sharing similar production structures. $R0_{i,g}$ 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 11: 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)
$R0\_bin0_{c,\{t-m,m\geq 3\}}$	-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)
$R0\_bin1_{c,\{t-m,m\geq 3\}}$	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

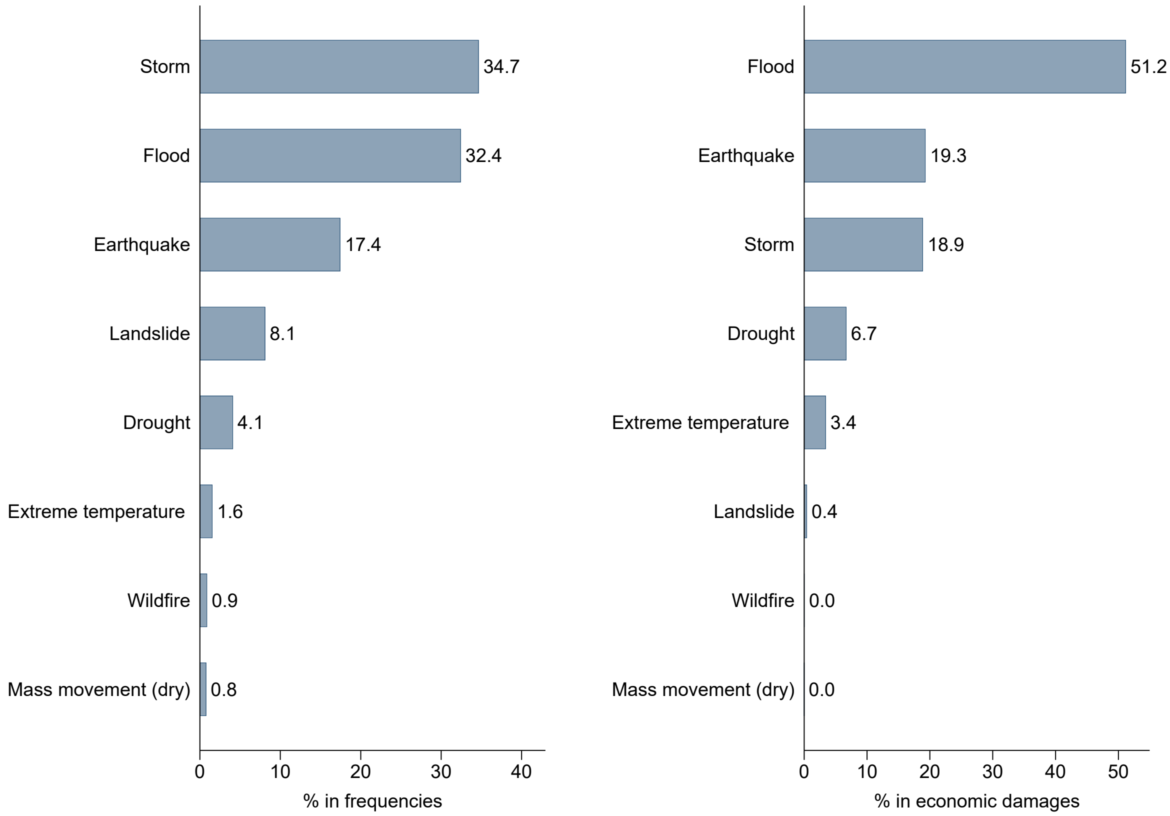
Notes: The table reports the inundation effects on firm entry and exit behaviour in county level. The dependent variables R_{exit}, R_{entry}, ln (#exit), and ln (#entry) are exit rate, entry rate, the number of exit firms (in logarithms), and the number of entrants (in logarithms), respectively. We 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 12: 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

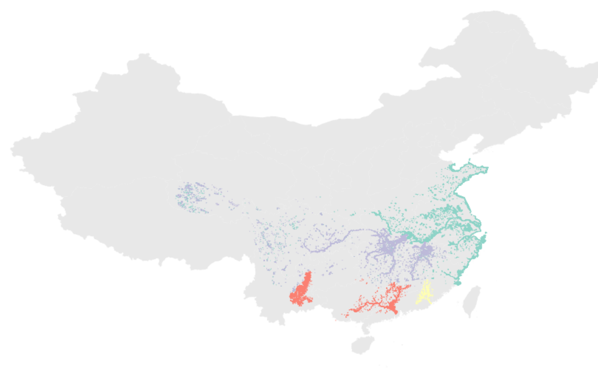


Notes: The figure illustrates the percentage shares of each type of natural disaster in terms of frequency (left panel) and economic damages caused (right panel) among all the disasters that occurred in mainland China from 1970 to 2021.

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

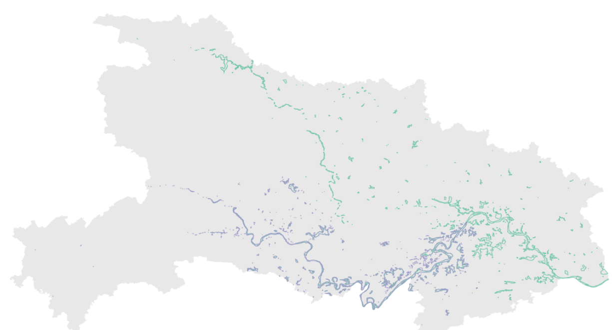
(A) DFO inundation areas in 2002

(B) GFD inundation areas in 2002



(C) DFO 2002: Zoom in to Hubei province

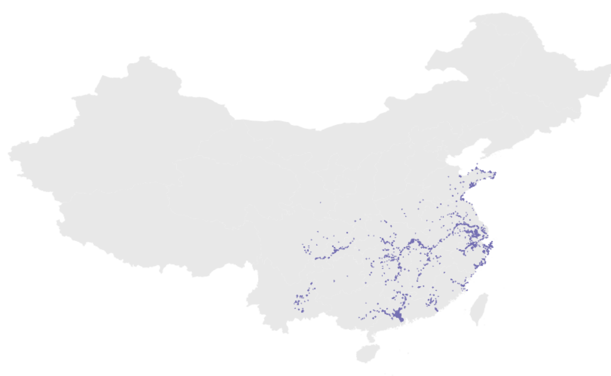
(D) GFD 2002: Zoom in to Hubei province



(E) DFO inundated firms in 2002

(F) GFD inundated firms in 2002

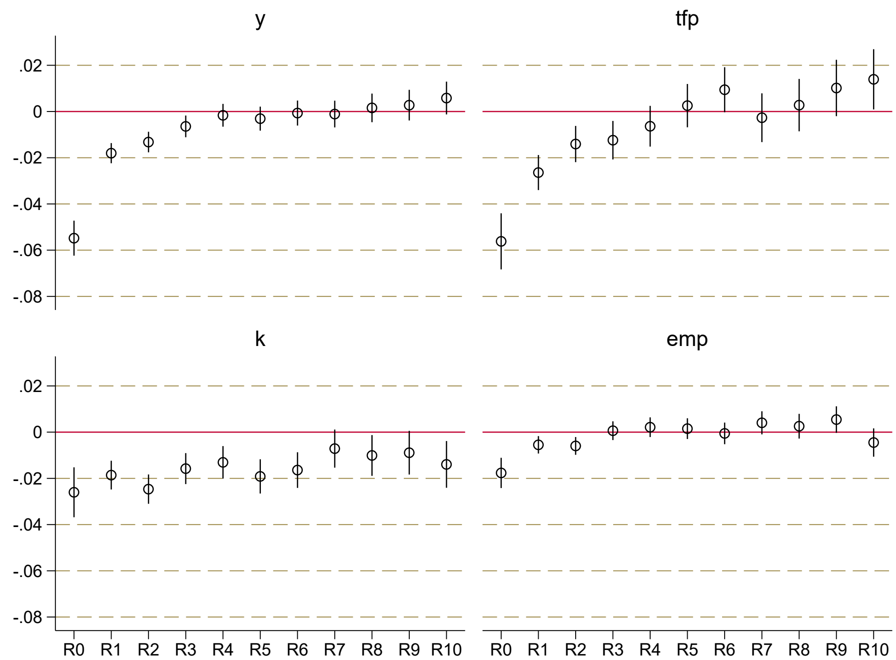
(G) GFD inundated+Adjacent 1km firms in 2002



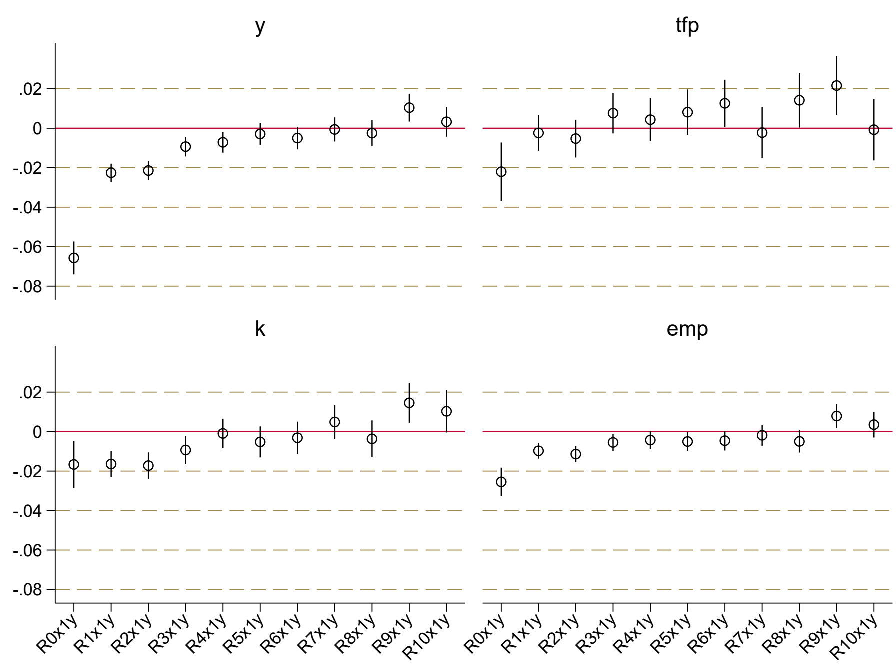
Notes: The figures plot the inundation areas and the corresponding inundated firms on Chinese map for the 4 successfully mapped flood events (from the satellite images) occurred in 2002. Panels (A) and (B) are the inundation areas according to DFO and GFD, respectively. Each color represents one flood 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

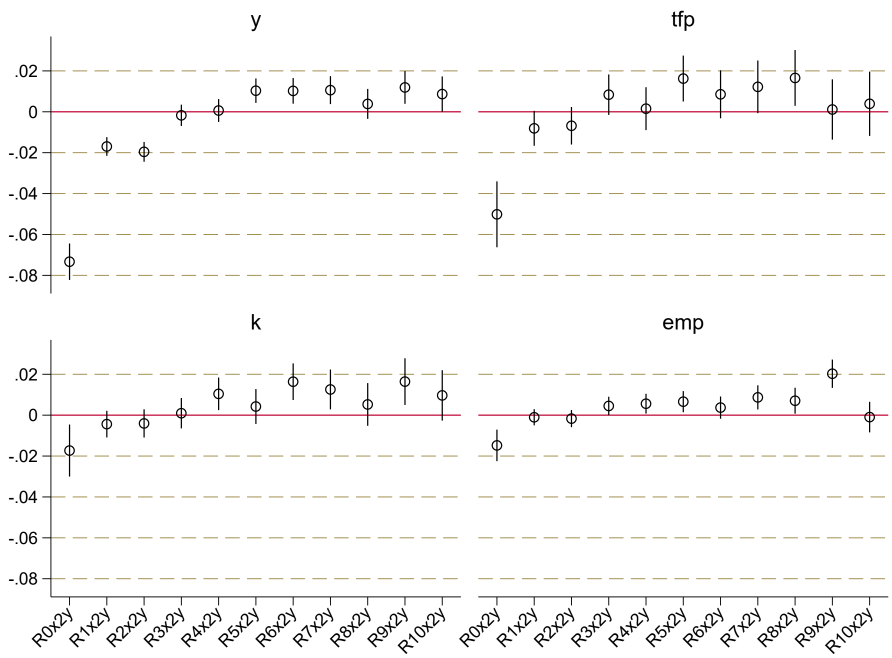
(A) Contemporaneous Effects



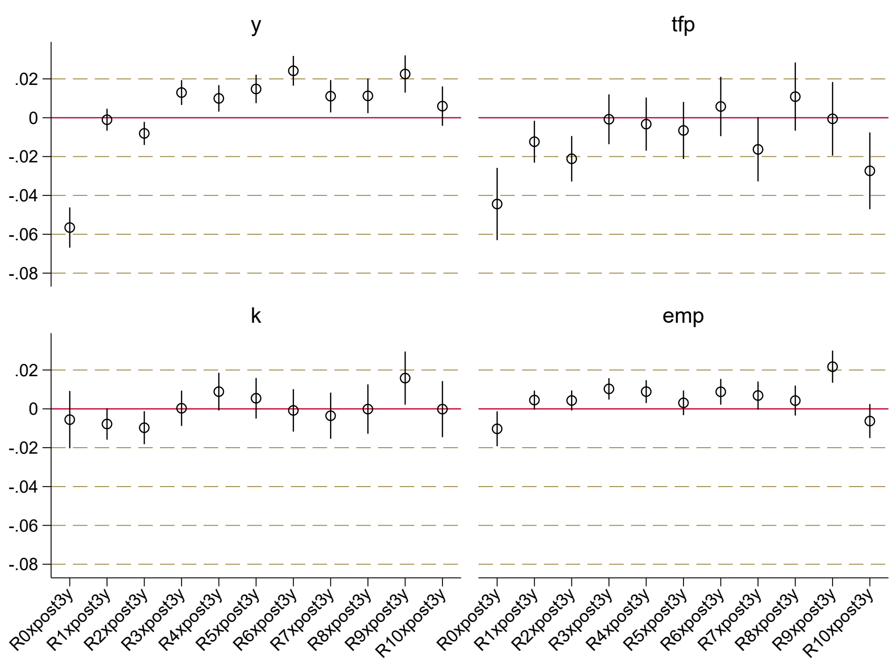
(B) 1-year Lagged Effects



(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.