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# Dissertation on the impacts of floods and trade war on the Chinese economy

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DISSERTATION ON THE IMPACTS OF FLOODS AND TRADE WAR

ON THE CHINESE ECONOMY

By

FAN ZHENG

A DISSERTATION

In

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Presented to the Singapore Management University in Partial Fulfilment

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PhD in Economics, Programme Director

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Submitted to the School of Economics in Partial Fulfilment of the
Requirements for the Degree of Doctor of Philosophy in Economics

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# Abstract

In the first chapter of the dissertation, we study the impact of floods on microlevel firm performances in China for the period 2000-2009. Among the first in the literature, we identify the flood exposure directly at the firm level by combining the high-resolution satellite-observed inundation areas with the geocoded firm locations. We find that being hit by a flood is associated with an annual loss to output and productivity of around 6% and 5%, respectively, which persists in the long run. The impacts of floods extend to non-inundated firms in neighborhoods (of 4 kilometres in radius), but the negative effects are much smaller (2% on average) and diminish after three years. Firms in the surrounding area but located beyond the immediate neighborhood expand their output from the third year onwards, in contrast with the permanent shrinkage of the inundated firms. For inundated firms, the aggregate output losses in the immediate year of and one year after the flood are estimated to be 165.5 billion RMB (0.12% of total GDP) and 200 billion RMB (0.15% of GDP), respectively, across years 2000-2009. In the second chapter, we follow the micro-to-macro approach of Fajgelbaum et al. (2020) to analyze the impacts of the 2018-2019 U.S.-China trade war on the Chinese economy. We use highly disaggregated trade and tariff data with monthly frequency to identify the demand/supply elasticities of Chinese imports/exports, combined with a general equilibrium model for the Chinese economy (that takes into account input-output linkages, and regional heterogeneity in employment and sector specialization) to quantify the partial and general equilibrium effects of the tariff war. In the third chapter, we extend the China-ROW setup discussed above to a China-U.S.-ROW framework that incorporates general equilibrium adjustments in both the Chinese and the US economies in response to the trade war. We further explore the role of input-output linkage in transmitting the impacts by conducting counterfactual analyses in which we allow

the tariff policies to be implemented sector by sector. The aggregate loss to the Chinese economy was estimated to be \$54.5 billion (0.44% of 2017 GDP), which is twice the loss experienced by the U.S. economy (\$27.7 billion). In contrast to the result that the U.S. consumers of imported goods took most of the losses, the majority of the adverse impacts on the Chinese side was borne by its exporters: The MFN tariff cuts implemented by the Chinese government helped cushion the negative impacts on its importers substantially, but at the cost of its producers, resulting in an overall larger aggregate loss.

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Last but not least, I am deeply grateful to my family for their unconditional love and support throughout my academic journey. Their unwavering belief in my abilities has been a constant source of motivation and inspiration.

# Dedication

This dissertation is dedicated to Mr. Zheng Fan as a summary of the six-year academic journey at SMU in Singapore.

# Chapter 1

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

## 1.1 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 1.1 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 et al. 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, 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 inunda-

[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.

tion 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 et al. (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 1.2.

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 2.4. In Section 1.4, 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.

### 1.1.1 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 et al. 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

[3] Almost all the literature listed above are of this type. This is very common for studies on temperature and precipitation. For example, Somanathan et al. (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.

the measurement error problem.

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

## 1.2 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.

### 1.2.1 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 et al. (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

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

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 1.1, 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 may run the counter risk of incomplete cov-

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

erage 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 1.2 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.

### 1.2.2 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 1.2.1 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

[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.

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 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.

### 1.2.3 Customs Data

In one set of analyses below in Section 2.4, 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.

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

## 1.3 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:

$$Y_{ipst} = \beta_0 R0_{i,t} + \beta_1 R0_{i,t-1} + \beta_2 R0_{i,t-2} + \beta_3 R0_{i,\{t-m,m\geq 3\}} + \lambda X_{i,t-1} + \delta_i + \delta_{pt} + \delta_{st} + \varepsilon_{ipst}, \tag{1.1}$$

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 $\beta_k$ 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 in periods $(t-m)$ for $m \geq 3$; the coefficient $\beta_3$ 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.

[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 1.2.

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, $\delta_i$, 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 1.1, 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 1.4, 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 1.2 reports the estimation results based on Equation 1.1 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 1.1, 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 1.1 as the baseline for the subsequent analyses.

The preliminary results based on Equation 1.1 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 1.1.1, 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.

### 1.3.1 Spillover Effects

We now generalize the specification in Equation 1.1 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:

$$\begin{aligned} Y_{ipst} = \sum_{k=0}^{10} \left(\beta_{0,Rk} Rk_{i,t} + \beta_{1,Rk} Rk_{i,t-1} + \beta_{2,Rk} Rk_{i,t-2} + \beta_{3,Rk} Rk_{i,\{t-m,m\geq 3\}}\right) \\ + \lambda X_{i,t-1} + \delta_i + \delta_{pt} + \delta_{st} + \varepsilon_{ipst}, \end{aligned} \tag{1.2}$$

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 1.1, 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 1.1.

Table 1.3 reports the inundation effects based on Equation 1.2, in comparison with the preliminary results based on Equation 1.1. 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 1.3 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 1.1, as seen in Table 1.3. This is a reinforcing evidence of spillover effects. As such, in the estimations below, we adopt Equation 1.2 as our baseline specification and explicitly control for potential spillover effects on firms in the neighborhoods within 20 kilometres ($R$1-10) of inundation areas.

### 1.3.2 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 1.2. All these analyses are conducted expanding on the baseline specification of Equation 1.2.

#### 1.3.2.1. 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 1.4 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).

### 1.3.2.2. Inventory Management

Natural disasters are usually low-probability but high-impact events for individual firms, and could cause supply chain disruptions (Carvalho et al. 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 1.5. 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

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

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.

#### 1.3.2.3. 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 1.3.2.1.

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 et al. 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 (25.9%) firms changed their ownership type.[11] We append the specification of Equation 1.2 with the interaction terms of the treatment dummies and the SOE indicator.

Table 1.6 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

[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).

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 1.4 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 1.4, 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 1.4. 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.

#### 1.3.2.4. 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 1.2 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 they are located in flood-prone counties or not) to avoid confounding mechanisms and interpretations.

[12] As shown in Figure 1.2, 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.

As shown in Table 1.7, 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 1.3 mask important heterogeneity across firms in terms of preparedness to floods.

#### 1.3.2.5. 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 1.8. 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 1.9, 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

[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.

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 1.8–1.9, the effects on import activities tend to mirror those on the export activities, suggesting a strong correlation of the two activities at the firm level.

#### 1.3.2.6. 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 1.2 sector by sector (dropping the original sector-year fixed effect controls). The results are reported in Table 1.10, 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.

### 1.3.3 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 et al. (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 exit for the period 2000–2009. In particular, we estimate the following specification:

$$\begin{aligned} Y_{crt} = \sum_{j, j \in \{0,1\}} \big( & \beta_{0,bj} R0\_binj_{c,t} + \beta_{1,bj} R0\_binj_{c,t-1} + \beta_{2,bj} R0\_binj_{c,t-2} \\ & + \beta_{3,bj} R0\_binj_{c,\{t-m, m \geq 3\}} \big) + \delta_c + \delta_{rt} + \varepsilon_{crt}, \end{aligned} \tag{1.3}$$

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 $\delta_c$ are included to control for any time-invariant county characteristics, and the prefecture-time fixed effects $\delta_{rt}$ to control for higher administrative-level shocks that are common to the counties in a prefecture-year.

The results are reported in Table 1.11. 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

[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 1.2.

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.

## 1.4 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 1.2.

As suggested by the analysis in Section 1.3.3, 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 1.12 reports the results given the restricted sample. In comparison with the baseline estimates (in the first column, repeated from Table 1.3), 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 1.12 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.

## 1.5 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 et al. (2020) and Gandhi et al. (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.

[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 1.1: 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 1.2: 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 ($R$1-10) | 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 1.3: 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) |
| $R0_{i,\{t-m,m\geq3\}}$ | -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 1.2. 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 $R0_{i,\{t-m,m\geq3\}}$ 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. 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 1.4: Heterogeneous Effects by Asset Structure

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

*Notes:* The table reports the heterogeneous effects among firms with different intensity of tangible assets. $R0_{i,g}$ is equal to 1 if firm $i$ is inundated in year $g$, thus the coefficients for $R0_{i,t}$, $R0_{i,t-1}$, $R0_{i,t-2}$, and $R0_{i,\{t-m,m\geq3\}}$ can be interpreted as contemporaneous effect, 1-year lagged effect, 2-year lagged effect, and long-run (3-year onwards) lagged effect of inundation, respectively. $Tangibility_i$ is equal to 1 if firm $i$ is tangible-intensive for at least half of the time for which it appears in the sample. A firm $i$ is said to be tangible-intensive in year $t$ if its share of tangible assets in total assets is above the 90 percentile across all firms in that year. Tangible assets refers to the fixed assets and inventory. We explicitly include neighbouring non-inundated firms within 20 kilometres from the inundation areas ($R$1-10) 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 1.5: 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 ($R$1-10) | 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 1.3.2.2. $R0_{i,g}$ 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 ($R$1-10) 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 1.6: 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) |
| $R0_{i,\{t-m,m\geq 3\}}$ | -0.0510*** | 0.0019 | -0.0087 | -0.0385*** |
| | (0.0065) | (0.0093) | (0.0056) | (0.0118) |
| $R0_{i,t} \times SOE$ | -0.0394*** | -0.0252 | -0.0034 | -0.0269 |
| | (0.0118) | (0.0168) | (0.0102) | (0.0188) |
| $R0_{i,t-1} \times SOE$ | -0.0520*** | -0.0331 | -0.0370*** | -0.0509** |
| | (0.0146) | (0.0208) | (0.0126) | (0.0243) |
| $R0_{i,t-2} \times SOE$ | -0.0648*** | -0.0432* | -0.0250 | -0.0757** |
| | (0.0178) | (0.0253) | (0.0153) | (0.0306) |
| $R0_{i,\{t-m,m\geq 3\}} \times SOE$ | -0.0872*** | -0.0761*** | -0.0183 | -0.0614 |
| | (0.0204) | (0.0291) | (0.0176) | (0.0381) |
| $SOE_{i,t}$ | -0.0293*** | 0.0651*** | 0.0306*** | -0.0634*** |
| | (0.0058) | (0.0083) | (0.0050) | (0.0096) |
| Observations | 1,255,386 | 1,255,386 | 1,255,386 | 808,893 |
| Number of Panel_id | 350,444 | 350,444 | 350,444 | 270,569 |
| Control for Spillovers ($R$1-10) | YES | YES | YES | YES |
| Firm FE | YES | YES | YES | YES |
| Sector×Year FE | YES | YES | YES | YES |
| Province×Year FE | YES | YES | YES | YES |
| Firms of Single Treatment | YES | YES | YES | YES |
| Firms of Multiple Treatments | NO | NO | NO | NO |
| Sample Period | 2000-09 | 2000-09 | 2000-09 | 2000-07 |

*Notes:* The table reports the heterogeneous effects among firms with different ownership structure. $R0_{i,g}$ is equal to 1 if firm $i$ is inundated in year $g$, thus the coefficients for $R0_{i,t}$, $R0_{i,t-1}$, $R0_{i,t-2}$, and $R0_{i,\{t-m,m\geq 3\}}$ can be interpreted as contemporaneous effect, 1-year lagged effect, 2-year lagged effect, and long-run (3-year onwards) lagged effect of inundation, respectively. $SOE_{i,t}$ is equal to 1 if firm $i$ is state-owned in period $t$. We explicitly include neighbouring non-inundated firms within 20 kilometres from the inundation areas ($R$1-10) 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 1.7: 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 (*R*1-10) | 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 (*R*1-10) 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 1.8: 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) |
| $R0_{i,\{t-m,m\geq3\}}$ | -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) |
| $R0_{i,\{t-m,m\geq3\}} \times Ex/Importer_{i,t}$ | -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 ($R$1-10) | 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 $R0_{i,\{t-m,m\geq3\}}$ 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. $Ex/Importer_{i,t}$ 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 ($R$1-10) 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 1.9: 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 1.10: 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 (*R*1-10) | 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$\times$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 ($R$1-10) 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 1.11: Inundation Effects on Firm Entry/Exit

| | $R_{exit}$ | | $R_{entry}$ | | $\ln(\#\text{exit})$ | | $\ln(\#\text{entry})$ | |
|---|---|---|---|---|---|---|---|---|
| | (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) |
| $\ln(\#\text{firms})$ | | 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 |

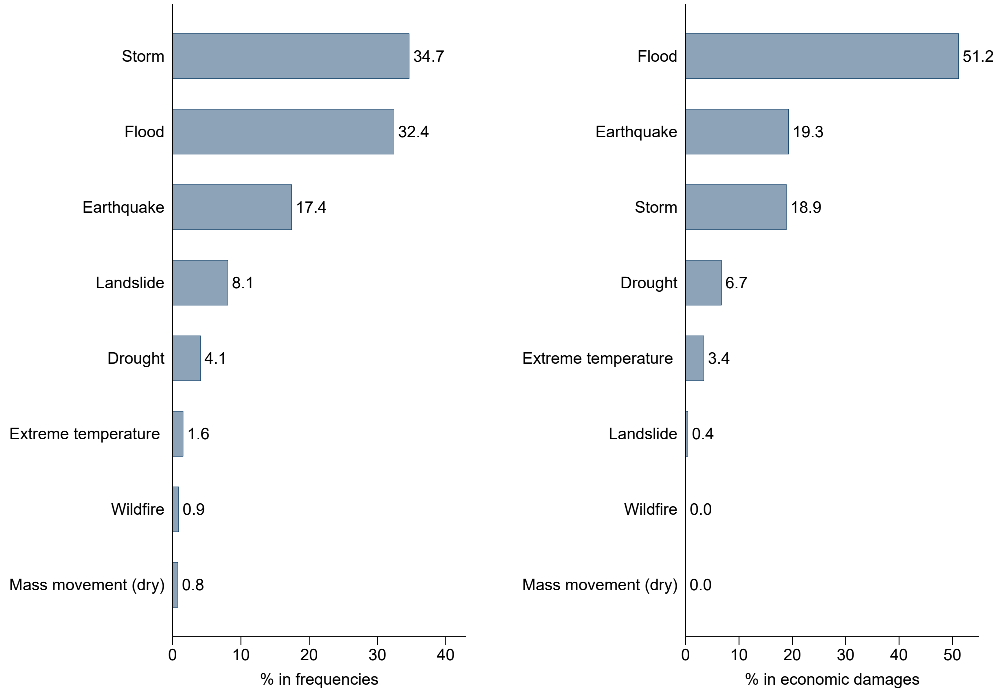
*Notes:* The table reports the inundation effects on firm entry and exit behaviour in county level. The dependent variables $R_{exit}$, $R_{entry}$, $\ln(\#\text{exit})$, and $\ln(\#\text{entry})$ are exit rate, entry rate, the number of exit firms (in logarithms), and the number of entrants (in logarithms), 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 1.12: 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 ($R$1-10) | 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 |

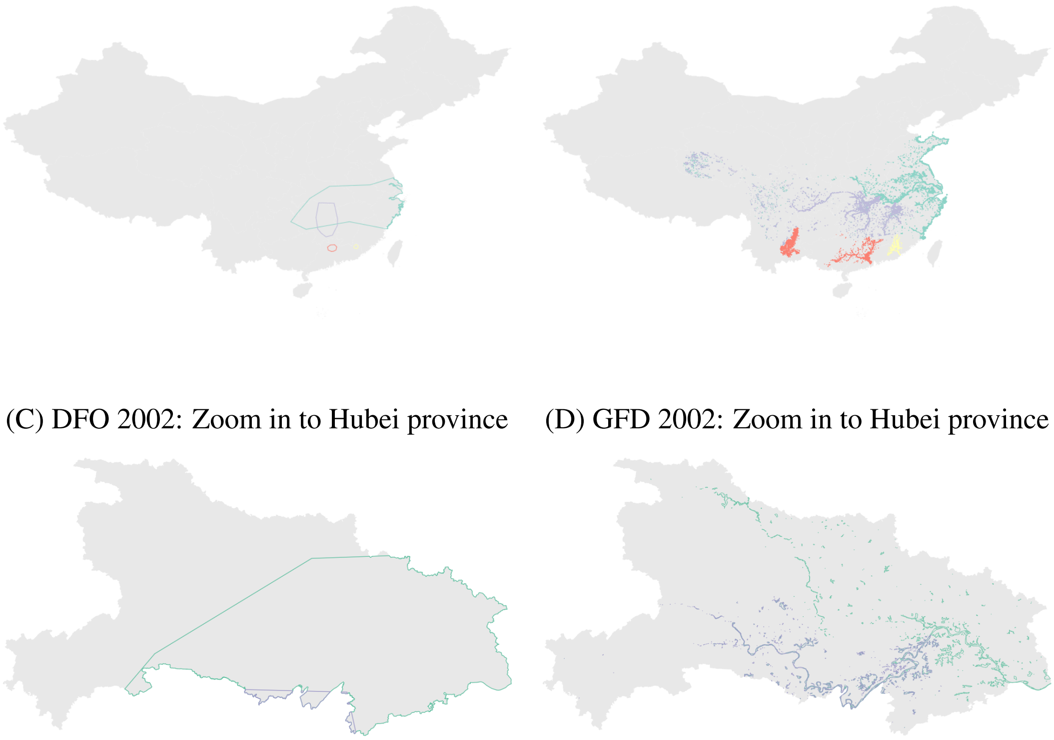
*Notes:* The table reports the estimation results when we use different subsamples as robustness checks. For each dependent variable, the first column under "Baseline" is the baseline estimates when we use the whole sample, as the same as the first columns under each dependent variable in Table 1.3. 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 ($R$1-10) 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 1.1: 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 1.2: Inundation Areas and Inundated Firms: GFD vs. DFO in 2002



(A) DFO inundation areas in 2002

(B) GFD inundation areas in 2002

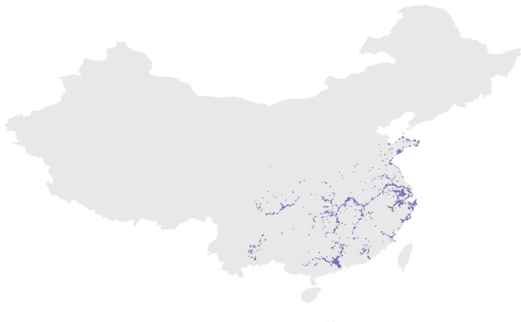
(C) DFO 2002: Zoom in to Hubei province

(D) GFD 2002: Zoom in to Hubei province

(E) DFO inundated firms in 2002

(F) GFD inundated firms in 2002

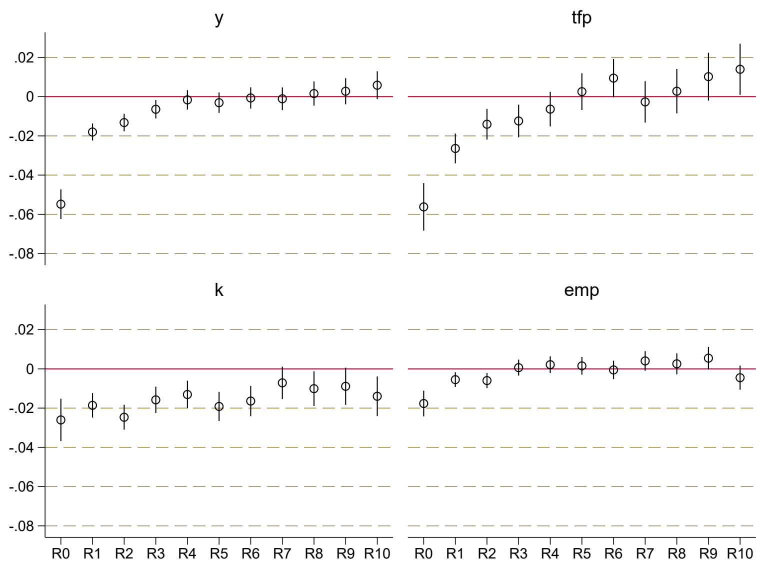
(G) GFD inundated+Adjacent 1km firms in 2002



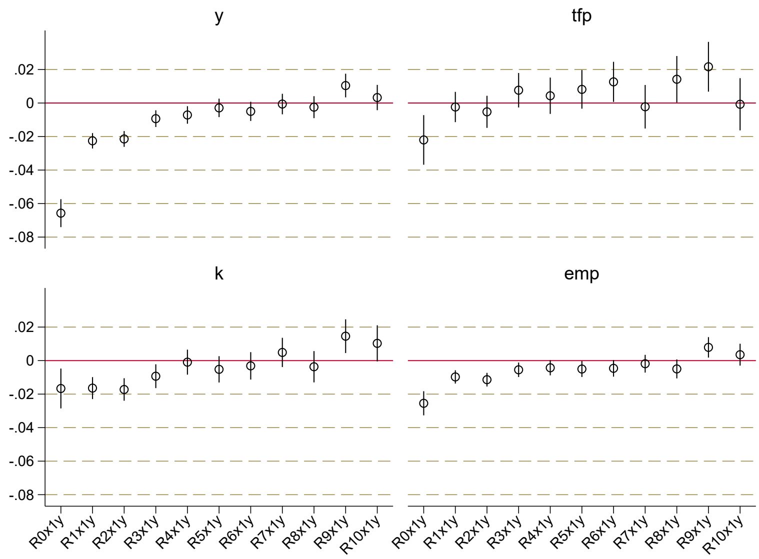
*Notes:* The figures plot the inundation areas and the corresponding inundated firms on Chinese map for the 4 successfully mapped flood events (from the satellite images) occurred in 2002. Panels (A) and (B) are the inundation areas according to DFO and GFD, respectively. Each color represents one flood 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 1.3: Spillover Effects on Neighbouring Non-inundated Firms

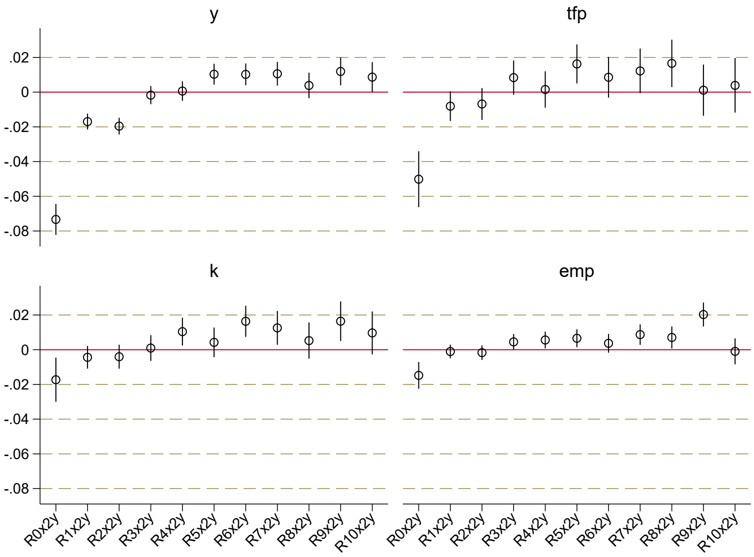
(A) Contemporaneous Effects



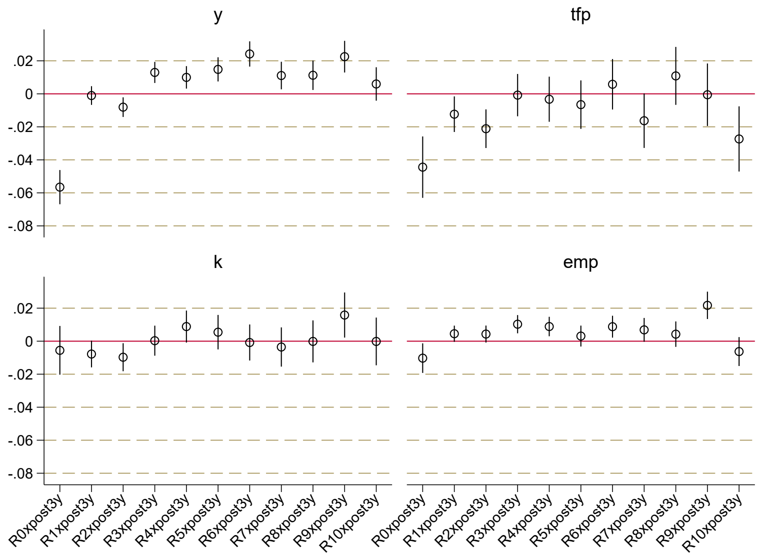

(B) 1-year Lagged Effects



(C) 2-year Lagged Effects




(D) Long-run Effects




*Notes:* The figure plots the estimates of the flooding effects on inundated firms (denoted as *R*0) 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 1.2. 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.

# Chapter 2

# The Response of the Chinese Economy to the U.S.-China Trade War: 2018–2019

## 2.1 Introduction

During 2018–2019, in an unprecedented manner since the 1930s, the U.S. Trump administration imposed seven rounds of tariff increases that affected Chinese exports. This includes the first round in February 2018, on solar panel and washing machine imports, and the second, targeting iron, aluminum and steel products. They were followed by three rounds of tariff hikes in 2018 and two in 2019, targeting imports specifically from China. All told, these seven rounds of tariff increases affected \$325.1 billion (14.27%) of Chinese exports across 6428 HS-8 products (using 2017 pre-war trade values). The U.S. statutory tariff rate on these Chinese products increased from 3.55% to 28.53% (simple average).

In return, China raised tariffs on U.S. products (four rounds in 2018 and two in 2019). All told, 5833 distinct HS-8 products imported from the U.S. were targeted during the period 2018:1–2019:12. In 2017 trade values, these affected \$109.3 billion (or 5.93%) of Chinese imports. The retaliation tariff rate increased from 6.46% to 21.27% (simple average). As China raised its tariffs against U.S. products, it also unilaterally lowered its Most-Favored-Nation (MFN) tariff rates on imports from non-U.S. sources where the MFN rate applied. This took place in four rounds during 2018:5–11. All told, the lists covered 3054 products, with a pre-war trade value of \$145.7 billion (or 7.90% of Chinese imports in 2017). The tariff rate across these products decreased from 9.89% to 6.82% (simple average).

In the literature, Amiti et al. (2019), Flaaen et al. (2020), Fajgelbaum et al. (2020), and Cavallo et al. (2021) have evaluated the ex-post impacts on the U.S. economy of the 2018–2019 trade war (in terms of prices, import/export quantities, real wages, or welfare), given events up to 2018:12, 2019:1, 2019:4, and 2020:2, respectively. These studies generally employed highly disaggregated product and tariff line classifications, with a strong focus on identifying the U.S. demand and supply structure at the micro product/variety level and their corresponding elasticities. On the other hand, studies by Charbonneau and Landry (2018), Guo et al. (2018) and Itakura (2020) conducted ex ante predictions of the trade-war effects using, respectively, the quantitative models of Caliendo and Parro (2015) and the GTAP CGE model (based on tariff changes imposed in the early phase of the trade war and/or proposed tariff changes at the time of their studies). Given the nature of their modeling frameworks, the trade and tariff changes are typically organized at the sector level, with emphasis on general equilibrium adjustment across sectors and countries. Li et al. (2020) similarly examined the welfare impacts of the trade war based on the GTAP model, but with analysis incorporating the tariff revisions as of 2020:3 (after the Phase One Deal was reached between the U.S. and China on December 13, 2019). The trade elasticities used in these studies were often taken from the literature based on sector-level trade analysis, or built-in parameters assumed by the GTAP models.

In this paper, we follow the micro-to-macro approach of Fajgelbaum et al. (2020), but with China now modeled as the local economy (given a detailed general equilibrium structure), while each of its trading partners is modeled in reduced form. Corresponding to the setup of Fajgelbaum et al. (2020) for the U.S. economy, the demand system we estimate for the Chinese economy includes reallocations between the domestic bundle and the imported bundle within each sector (defined as a 2-digit GB/T code, a standard Chinese industry classification system), across products (defined as 8-digit HS product codes) within each sector's imported bundle, and across varieties (defined as country-product pairs) within each imported product. This demand system is interacted with foreign export supply at the variety level, and their joint effects on prices and quantities are aggregated up the hierarchy of demand to the product and sector levels. In contrast, the import demand and export supply structures for each of China's trading partners are specified/identified only at the variety level.

To estimate this system, we compile data on China's imports (exports) from (to) each of its trading partners, in terms of both quantities and values at the 8-digit HS level, with monthly frequency for the period 2017:1–2019:12. We similarly compile the Chinese tariff rates on imports with respect to each trading partner (at the HS-8 level), and the foreign tariff rates on China's exports (at the HS-6 digit level), with monthly frequency for the same period. These are constructed using the baseline statutory tariff rates that were in place at the start of 2017, amended with tariff changes announced by the Ministry of Finance, China, or the U.S. Trade Representative during the period studied.

As suggested by Fajgelbaum et al. (2020) and Zoutman et al. (2018), the import demand and foreign export supply elasticities can be identified simultaneously using changes in tariffs as an instrument, provided that these changes are uncorrelated with demand and supply shocks. We conduct tests to verify the validity of this condition from the Chinese economy's perspective, based on tariff shocks associated with the trade war during the period 2018:1–2019:12. Tables 2.3 and 2.6 report the variety-level estimation results, and Tables 2.4–2.5 the product-level and sector-level estimation results. Overall, the elasticities we estimate for the Chinese economy are smaller in magnitude than the U.S. counterparts obtained by Fajgelbaum et al. (2020). Table A.1 summarizes the partial (direct) impacts on Chinese imports and exports, given the elasticity estimates and the tariff changes due to the trade war. Chinese imports of U.S. products targeted by the Chinese import tariff fell by 13.14% (weighted average). The MFN tariff cuts extended by China cushioned the negative impacts substantially. Chinese imports from these non-U.S. MFN sources of imports are estimated to have increased by 3.48% for targeted varieties. With the opposing effects combined, the overall change in Chinese imports of targeted varieties was muted at $-3.64\%$. On the other hand, exports of Chinese products targeted by the U.S. tariffs fell by $-24.48\%$. Thus, the major brunt of the tariff war on the Chinese economy was borne by its exports in partial equilibrium.

We then simulate for the Chinese economy the general equilibrium effects of the tariff shocks, given the elasticity parameters estimated above (at variety/product/sector level), and a supply-side structure calibrated to the observed labor allocation across Chinese sector-provinces, input-output structures across sectors, consumption allocation across non-tradable and tradable sectors, capital/labor/intermediate cost shares in sector-level production, and imports and exports across varieties. The system is large in dimension, including endogenous prices for each variety, product, and sector, wages for each sector-province, and final and intermediate expenditures across sectors. Thus, as in Fajgelbaum et al. (2020), the system is solved as a first-order linear approximation in log changes around the pre-war equilibrium in 2017, given the China-U.S. tariff shocks during 2018:1–2019:12.

Table 2.8 summarizes the effects on producers/exporters ($EV^X$), consumers/buyers of imports ($EV^M$), and tariff revenue ($\Delta R$) in Columns (1)–(3) and the aggregate impacts in Column (4). Our analysis suggests large negative consequences of the trade war on both Chinese producers ($-0.272\%$ of China's GDP) and consumers ($-0.057\%$ of GDP), with the producers (exporters) suffering more than four times the loss of the buyers of imports. Both components further dominate the positive tariff revenue increase. As a result of the trade war, China sustained an aggregate loss of \$37.898 billion, or 0.312% of its GDP. Without counter-retaliation, its loss would have been much larger, at \$38.921 billion (0.321% of GDP), and would have been largely borne by producers (exporters). The retaliation against the U.S. imports shifted the burden to the Chinese buyers of imports. Further adjustment in the MFN tariff rates on non-U.S. imports lessened the loss of Chinese buyers of imports and shifted part of the burden back to the producers. Overall, the aggregate loss is significant statistically. In comparison, Fajgelbaum et al. (2020) reported much larger consumer loss ($-0.27\%$ of U.S. GDP), a positive effect on producers (0.05% of U.S. GDP), and only slightly negative aggregate effect ($-0.04\%$ of U.S. GDP) for the U.S. economy.

We then analyze the variation in exposure to the trade war across provinces in China. For this purpose, we construct the province-level exposure of tradable sectors by first computing the trade-weighted tariff changes for each GB/T-2 sector and then mapping them to provinces based on provincial employment structure. Figure 2.3 suggests that China tended to: (A) retaliate against the U.S. in sectors with a relatively high concentration in the outlying provinces such as Xinjiang, Hainan, and Heilongjiang; and (B) reduce MFN tariffs on sectors concentrated in provinces closer to the coast, such as Shanghai and Beijing. Overall, China's tariff increases tended to be biased toward inner provinces and turn negative in the Eastern provinces. Added to the burden, Panel (D) suggests that these provinces also faced higher tariff increase on their exports to the U.S.

Figure 2.4 summarizes the simulated effects of the trade war on real wage across provinces in general equilibrium. Every province experienced a reduction in the tradable real wage. Provinces with larger relative losses are concentrated in the Southeast, whose employment structures were hit more strongly by the U.S. tariff increase. The real wage losses would have been one level higher without the MFN tariff cuts by China. This contrasts with the finding in Table 2.8, where the MFN tariff cuts by China worsened the aggregate loss. This implies that the MFN tariff cuts helped cushion the impacts on workers/consumers via lower import prices, at the cost of producers (and the owners of capital and fixed structures), who faced greater competition in the product market. Overall, on average across provinces, the nominal wages for workers in tradable sectors decreased by 3.19%. These income losses were, however, cushioned by a lower cost of living, as the CPI of tradable goods decreased by 2.34% on average across sectors. As a result, real wages in the tradable sector fell by 0.32%.

The remainder of the paper is structured as follows. Section 2.2 documents the data used for the analysis and the timeline of the tariff events. Section 2.3 outlines the economic structure used for the analysis. Section 2.4 presents the estimation results of elasticities and partial equilibrium impacts on trade. Section 2.5 reports the simulated general equilibrium effects at the aggregate, across Chinese provinces, and across sources of imports and destination of exports. Section 2.6 concludes.

## 2.2 Data and Timeline

### 2.2.1 Data

We obtained the Chinese baseline tariff rates from the UN TRAINS database and its tariff rate changes from the Ministry of Finance, China. The former is available at the 10-digit Harmonized System (HS) level and the data were aggregated and matched to the latter, available at the HS-8 level. Starting with the baseline import tariff rate in January 2017, we update the rates at monthly frequency, given the official announcement by the Ministry of Finance, China, of any tariff changes. Note, however, that only tariff changes announced in association with the tariff war are used as sources of variations in the instrumental variable to identify the import demand and export supply elasticities.

We similarly obtained the baseline tariff faced by Chinese exports from the UN TRAINS database. These data are harmonized across countries up to the HS-6 digit level. The information on the U.S. tariff increase associated with the trade war is based on Fajgelbaum et al. (2019) (for tariff changes in 2018) and the Office of the United States Trade Representative (USTR) (for tariff changes in 2019). The tariff changes are aggregated from the HS-10 to the HS-6 level by simple averaging. The estimations of trade elasticities for Chinese exports are nonetheless conducted at the HS-8 level of trade (with the HS-6 tariffs assigned to all HS-8 products in the category). Because we work with monthly data and the tariff changes could be implemented anytime within a month, we scale the tariff changes by the number of days of the month they were in effect.

We obtained China's trade data with monthly frequency for the period 2017:1–2019:12 from the General Administration of Customs, China. The data on Chinese imports and exports are available at the HS-8 digit level (which we refer to as products) by the source of imports and the destination of exports. Country-product pairs are referred to as varieties. For each variety, the customs data report the quantities of imports and exports, the value of imports at the CIF price, and the value of exports at the FOB price. The import and export values are reported in current US$ values.

We classify sectors using the China Industry Classification system (GB/T 4754), which is widely used for reporting official statistics on companies and organizations throughout Mainland China. The sector-level data at the GB/T 2-digit level (denoted GB/T-2) were obtained from China's National Bureau of Statistics. These include the producer price index for industrial products (PPI); the sectoral output in monthly frequency; and the input-output (IO) tables for 2017. For the analysis in the paper, we classify a GB/T-2 sector as tradable if it is matched to at least one HS-6 code of the trade classification.

For the general equilibrium analysis, we collected the annual employment and wage data at the sector and province level from the China Labor Statistical Yearbook of 2017. It records the employment and total wages of urban units by sector and province. These are available for 31 provinces and 94 GB/T-2 sectors (covering services, agriculture, mining and manufacturing). All 39 sectors identified as tradable are covered individually in both the IO tables and the labor statistics dataset. We aggregate the remaining sectors as a single non-tradable sector, reconciling the IO tables and the labor statistics dataset. More details about the data are provided in Appendix 2.6.

### 2.2.2 Timeline

Table 2.1 reports the list of tariff events enacted by the U.S. (Panel A) and China (Panel B1 and B2) during the period 2018:1–2019:12 of the trade war. For each tariff event, we identify the number of HS-8 products targeted and the quantum (and percentages) of Chinese exports and imports (in million US$) affected by the U.S. and Chinese tariff changes, respectively, based on 2017 pre-war trade flows. We summarize the extent of tariff changes in each event by the simple average of tariff rates (in percentage points) across targeted products before and after the implementation. Figure 2.1 illustrates the timing and the tariff changes.[1]

Panel A of Table 2.1 reports the seven waves of U.S. statutory tariff increases that affected Chinese exports during the period. This includes the first wave of tariff increases in February 2018 applied to solar panel and washing machine imports, and the second wave of tariffs, which targeted iron, aluminum, and steel products. They were followed by three tranches of tariff hikes in 2018 and two tranches in 2019, targeting imports specifically from China. In total, these seven rounds of

[1] In estimations and welfare analysis, the tariff changes applicable to a month are scaled by the number of days the changes were in effect in a month. Refer to the Data Appendix for additional details. For illustration purposes only, in Table 2.1 and Figure 2.1, the implementation month is taken to be the current month if the implementation date is before the 15th of the month and the next month otherwise. The 'before' and 'after' simple monthly average tariff rates correspond to those in the month before and the month after the implementation month.

tariff increase covered \$325.1 billion (14.27%) of total Chinese exports across 6428 HS-8 products (using 2017 pre-war trade flows). The average U.S. statutory tariff rate on these Chinese products increased from 3.55% to 28.53%.

Panel B1 of Table 2.1 lists the seven rounds of China's retaliatory tariffs on U.S. products. All told, 5833 distinct HS-8 products imported from the U.S. were targeted. In 2017 trade values, these affected \$109.3 billion (or 5.93%) of Chinese imports. The average retaliation tariff rate increased from 6.46% to 21.27%. The first wave of tariff increases by China against imports from the U.S. was enacted on April 2, 2018. China increased the tariff (by 15%–25%) on U.S. products (worth about \$3 billion), including fruit, wine, seamless steel pipes, pork and recycled aluminum, in response to the U.S. steel and aluminum tariffs. In July and August 2018, China implemented two rounds of retaliatory tariff increases (by 25%) on U.S. products, including agricultural products, automobiles and aquatic products (List 1), and commodities such as coal, copper scrap, fuel, buses and medical equipment (List 2), respectively. In September 2018, China continued to respond to U.S. tariffs and enacted another round of tariff increases on about \$60 billion worth of U.S. goods (List 3). In January 2019, China revised its lists and exempted U.S. autos (from an extra 25% tariff) and certain U.S. auto parts (from an extra 5% tariff). But as the tariff war escalated, in June and September 2019, China further increased tariffs on more than \$68 billion worth of products imported from the U.S.

As China raised its tariffs against the U.S. products, it also unilaterally lowered its MFN tariff rates on imports from non-U.S. sources where MFN rates apply. Panel B2 of Table 2.1 summarizes four waves of China's MFN tariff cuts in May to November 2018. Products affected included pharmaceuticals (May), autos and ITA products (July), a subset of consumer goods (July) and industrial goods (November). In total, the lists covered 3054 products, with a pre-war trade value of \$145.7 billion (or 7.90% of Chinese imports in 2017). The average tariff rate across these products decreased from 9.89% to 6.82%.

Table 2.2 reports the summary statistics for the extent of exposure to the tariff war by GB/T-2 codes. For Chinese imports, we report the number of targeted HS-8 products and varieties, and the means and standard deviations of tariff increases across targeted varieties within GB/T-2 codes. The Chinese sectors that received the most protection from tariff increases on U.S. products were agricultural products, chemicals, fuel, metals and waste resources. In contrast, the sectors of food, textiles, articles for cultural activities, and automobiles are shown to have been subject to MFN tariff cuts to a larger extent. On the export side, the table indicates that Chinese sectors that faced the largest tariff increases by the U.S. were metals, electrical equipment, machinery and computer products.

## 2.3 Economic Structure

In this section, we set up the economic structure à la Fajgelbaum et al. (2020). Sections 2.3.1–2.3.2 describe the demand/supply structure that guides the estimation in Section 2.4. Section 2.3.3 describes the full general equilibrium system that forms the basis of the welfare analysis in Section 2.5.

### 2.3.1 The Demand System and Preferences

Suppose there are $S$ tradable sectors indexed by $s$. Within each of these sectors, aggregate demand (from producers and consumers) follows a three-tier CES structure: in the first tier, goods are differentiated by domestic and imported bundles (denoted as $D_s$ and $M_s$ respectively) in each sector; in the second tier, they are differentiated by products (indexed by $g$) within the domestic or imported bundle; and in the third tier, by varieties (indexed by $ig$), differentiated by country of origin $i$ within each imported product category.

In particular, in the first tier, the demand from consumers for consumption ($C_s$) and the demand from producers for intermediate inputs ($I_s$) follow a CES structure:

$$C_s + I_s = \left( A_{Ds}^{\frac{1}{\kappa}} D_s^{\frac{\kappa-1}{\kappa}} + A_{Ms}^{\frac{1}{\kappa}} M_s^{\frac{\kappa-1}{\kappa}} \right)^{\frac{\kappa}{\kappa-1}}, \tag{2.1}$$

with an elasticity of substitution $\kappa$ between the domestic and imported bundles, and sector-level demand shifters ($A_{Ds}$ and $A_{Ms}$) for the domestic and imported bundles, respectively. This implies a sector-level price index: $P_s = \left( A_{Ds} P_{Ds}^{1-\kappa} + A_{Ms} P_{Ms}^{1-\kappa} \right)^{\frac{1}{1-\kappa}}$, given the price indices of domestic and imported bundles ($P_{Ds}$ and $P_{Ms}$) in sector $s$.

In the second tier, the domestic or imported bundle ($D_s$ or $M_s$) is each a CES aggregate of products within the sector ($d_g, m_g$), with an elasticity of substitution $\eta$

and demand shifter ($a_{Dg}$ and $a_{Mg}$, respectively) for $g \in \mathscr{G}_s$. This implies corresponding price indices ($P_{Ds}, P_{Ms}$), which are CES aggregates of, respectively, the prices of domestic and imported products ($p_{D_g}$ and $p_{M_g}$) for $g \in \mathscr{G}_s$.

Finally, in the third tier, each imported product ($m_g$) is further a CES aggregate of varieties ($m_{ig}$) differentiated by country of origin $i$, with an elasticity of substitution $\sigma$ and demand shifter $a_{ig}$:

$$m_g = \left( \sum_{i \in \mathscr{I}_g} a_{ig}^{\frac{1}{\sigma}} m_{ig}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}, \tag{2.2}$$

and a corresponding price index: $p_{Mg} = \left( \sum_i a_{ig} p_{ig}^{1-\sigma} \right)^{\frac{1}{1-\sigma}}$, given the variety price $p_{ig}$. The above demand system implies that the values of demand for domestic goods and imported goods in sector $s$ are:

$$P_{Ds} D_s = E_s A_{Ds} \left( \frac{P_{Ds}}{P_s} \right)^{1-\kappa}, \tag{2.3}$$

$$P_{Ms} M_s = E_s A_{Ms} \left( \frac{P_{Ms}}{P_s} \right)^{1-\kappa}, \tag{2.4}$$

where $E_s$ is the aggregate expenditure on goods of sector $s$. In turn, the value of imports for product $g$ in sector $s$ is:

$$p_{Mg} m_g = P_{Ms} M_s a_{Mg} \left( \frac{p_{Mg}}{P_{Ms}} \right)^{1-\eta}, \tag{2.5}$$

and the quantity imported of product $g$'s variety from country $i$ is:

$$m_{ig} = m_g a_{ig} \left( \frac{p_{ig}}{p_{Mg}} \right)^{-\sigma}. \tag{2.6}$$

Given the ad valorem tariff rate $\tau_{ig}$ imposed on a variety and the variety's CIF price $p_{ig}^*$ before tariff, the consumer price of the variety is:

$$p_{ig} = (1 + \tau_{ig}) p_{ig}^*. \tag{2.7}$$

In the general equilibrium, to study the regional effects of tariffs, we divide China into $R$ regions (effectively provinces). Each region is indexed by $r$ and the set of regions is denoted by $\mathscr{R}$. There is one non-tradable sector in addition to the set of tradable sectors described above. Tradable sectors are freely traded within China but subject to trade costs internationally. The representative consumer in each region $r$ is assumed to have a Cobb-Douglas preference for the non-tradable and tradable goods:

$$\beta_{NT} \ln C_{NT,r} + \sum_{s \in \mathscr{S}} \beta_s \ln C_{sr}, \tag{2.8}$$

where $C_{NT,r}$ is the consumption of the homogeneous non-tradable good, $C_{sr}$ is the consumption of the tradable goods of sector $s$, and the $\beta$'s sum to one. Consumers in a region $r$ face the price of the non-tradable good $P_{NT,r}$ and the price index $P_s$ for each sector $s$.

### 2.3.2 The Foreign Counterpart

For each trading partner, its export supply to China and its import demand for Chinese product at the variety level are specified as follows to fully characterize the international markets. For a product from country $i$, China faces an inverse foreign export-supply curve according to:

$$p^*_{ig} = z^*_{ig} m_{ig}^{\omega^*}, \tag{2.9}$$

where $z^*_{ig}$ is a foreign export supply shifter, and $\omega^*$ is the inverse foreign export supply elasticity. The larger $\omega^*$ is, the more China can extract a decrease in the supply price from the exporter and hence a larger potential gain from imposing import tariffs.

The foreign import demand for the variety from China of product $g$ is assumed to be similar to China's import variety demand:

$$x_{ig} = a^*_{ig} \left( \left(1 + \tau^*_{ig}\right) p^X_{ig} \right)^{-\sigma^*}, \tag{2.10}$$

where $x_{ig}$ is country $i$'s demand for product $g$ from China, $a^*_{ig}$ is a foreign import demand shifter, $\tau^*_{ig}$ is the ad valorem tariff set by country $i$ on China's exports of product $g$, $p^X_{ig}$ is China's export supply price of product $g$ to market $i$, and $\sigma^*$ is the corresponding foreign import demand elasticity.

### 2.3.3 The Supply-Side Structure

Production of tradable goods in each sector-region uses workers, intermediate inputs, and a fixed factor (capital and structures). In the short run, the primary factors of production (capital and labor) are assumed to be immobile across regions and sectors.[2] In particular, the production of tradable goods in a sector-region is assumed to be:

$$Q_{sr} = Z_{sr} \left( \frac{I_{sr}}{\alpha_{Is}} \right)^{\alpha_{Is}} \left( \frac{L_{sr}}{\alpha_{Ls}} \right)^{\alpha_{Ls}}, \tag{2.11}$$

where $Z_{sr}$ is the productivity of sector $s$ in region $r$, $I_{sr}$ is the use of intermediate input bundle, $L_{sr}$ is the labor input, and $\alpha_{Is}$ and $\alpha_{Ls}$ are the cost shares of intermediate goods and labor in total sales of sector $s$, respectively.

The intermediate input bundle used by sector $s$ is assumed to be a Cobb-Douglas aggregate of inputs from other sectors, with $\alpha_s^{s'}$ representing the share of input $s'$ in total sales of sector $s$. This implies that the cost of the intermediate input bundle used by sector $s$ is:

$$\phi_s \propto \prod_{s' \in S} P_{s'}^{\frac{\alpha_s^{s'}}{\alpha_{Is}}}. \tag{2.12}$$

The owners of the fixed factor choose inputs $I_{sr}$ and $L_{sr}$ to minimize the cost of production, given the cost of the intermediate input bundle $\phi_s$; the wage rate $w_{sr}$ in sector $s$ and region $r$; and the production target $Q_{sr}$. Given the producer price $p_s$ in sector $s$, the fixed factor owners then choose the production level $Q_{sr}$ that maximizes their profit:

$$\begin{aligned} \Pi_{sr} &\equiv \max_{Q_{sr}} p_s Q_{sr} - \phi_s I_{sr}(Q_{sr}) - w_{sr} L_{sr}(Q_{sr}) \\ &= \max_{Q_{sr}} p_s Q_{sr} - (1 - \alpha_{Ks}) \left( \frac{\phi_s^{\alpha_{Is}} w_{sr}^{\alpha_{Ls}}}{Z_{sr}} Q_{sr} \right)^{\frac{1}{1-\alpha_{Ks}}}, \end{aligned} \tag{2.13}$$

where $\alpha_{Ks} \equiv 1 - \alpha_{Is} - \alpha_{Ls}$ is the share of capital cost in total sales of sector $s$. This implies an optimal output choice as a function of output and factor prices:

$$Q_{sr} = Z_{sr}^{\frac{1}{\alpha_{Ks}}} p_s^{\frac{1-\alpha_{Ks}}{\alpha_{Ks}}} \phi_s^{-\frac{\alpha_{Is}}{\alpha_{Ks}}} w_{sr}^{-\frac{\alpha_{Ls}}{\alpha_{Ks}}}, \tag{2.14}$$

and the national production in sector $s$ as:

$$Q_s = \sum_{r \in \mathscr{R}} Q_{sr}. \tag{2.15}$$

The non-tradable sector is assumed to use only labor for production: $Q_r^{NT} = Z_r^{NT} L_r^{NT}$, where $Z_r^{NT}$ is the labor productivity of region $r$ in the non-tradable sector, and $L_r^{NT}$ is the employment in this sector in region $r$.

[2] Nonetheless, in deriving the system (in log changes), Appendix 2.6 also considers the scenario of labor mobility across sectors.

Output by sector $Q_s$ is assumed to be allocated across products $q_g$ at a constant marginal rate of transformation according to:

$$\sum_{g\in\mathscr{G}_s}\frac{q_g}{z_g}=Q_s, \tag{2.16}$$

where $z_g$ is a product-level productivity shock. Assuming perfect competition, this pins down the local price of the domestic variety of product $g$ at $p_{Dg}=\frac{p_s}{z_g}$. The price of the same variety when shipped to a foreign country $i$ is $p^X_{ig}=\delta_{ig}p_{Dg}$, given the iceberg trade cost factor $\delta_{ig}$. The market-clearing condition for the local variety of product $g$ requires that:

$$q_g=\underbrace{\left(a_{Dg}D_s\right)\left(\frac{p_{Dg}}{P_{Ds}}\right)^{-\eta}}_{d_g}+\sum_{i\in\mathscr{I}^X_g}\delta_{ig}\underbrace{a^*_{ig}\left(\left(1+\tau^*_{ig}\right)p^X_{ig}\right)^{-\sigma^*}}_{x_{ig}}. \tag{2.17}$$

Labor income and profits are assumed to be spent where they are generated. Total tariff revenue $R$ and national trade deficit $D$ are assumed to be distributed to each region in proportion to the population share $b_r$ of the region. Thus, by accounting identity, final expenditures in region $r$ are:

$$\begin{aligned}X_r &= w_{NT,r}L_{NT,r}+\sum_{s\in\mathscr{S}}w_{sr}L_{sr}+\sum_{s\in\mathscr{S}}\Pi_{sr}+b_r\left(D+R\right)\\ &= P_{NT,r}Q_{NT,r}+\sum_{s\in\mathscr{S}}\left(1-\alpha_{Is}\right)p_sQ_{sr}+b_r\left(D+R\right).\end{aligned} \tag{2.18}$$

Finally, the optimal output choice $Q_{sr}$ in (2.14) implies an (inverse) labor demand function in sector $s$ of region $r$:

$$w_{sr}=\left(\frac{Z_{sr}p_s}{\left(L_{sr}/\alpha_{Ls}\right)^{\alpha_{Ks}}\phi_s^{\alpha_{Is}}}\right)^{\frac{1}{1-\alpha_{Is}}}, \tag{2.19}$$

and an average wage for the tradable sectors in region $r$ of:

$$w^T_r=\frac{\sum_{s\in S}w_{sr}L_{sr}}{\sum_{s\in S}L_{sr}}. \tag{2.20}$$

The wage in the non-tradable sector is then pinned down by the market-clearing condition:

$$w^{NT}_r=\frac{\beta_{NT}X_r}{L^{NT}_r}. \tag{2.21}$$

A general equilibrium given tariffs consists of producer prices $\{p_s\}$, import prices $\{p^*_{ig}\}$, price indices $\{p_{Mg},P_{Ms},P_{Ds},P_s,\phi_s\}$, tradable sector wages $\{w_{sr}\}$ and non-tradable sector wages $\{w^{NT}_r\}$ such that (i) given these prices, consumers, producers and workers optimize their choices; (ii) domestic markets for final goods and intermediate inputs clear, international markets for imports and exports of every variety clear, and labor markets for every sector and region clear; and (iii) the government budget is balanced.

## 2.4 Identification and Estimation

In this section, we estimate the 3-tier demand system using the variation of import tariffs associated with the trade war as the instrument, and conduct pre-trend tests to support the validity of the instrument in Section 2.4.5.

### 2.4.1 Chinese import demand and foreign export supply elasticities at variety level ($\sigma$, $\omega^*$)

We use variation in the Chinese import tariffs as the instrument to estimate the Chinese import demand and foreign export supply elasticities at the variety level, in the same spirit as the work of Fajgelbaum et al. (2020) for the U.S. economy using the U.S. import tariffs. The approach is based on the argument (cf. Zoutman, Gavrilova and Hopland 2018) that if the tariff variations are uncorrelated with the unobserved import demand and export supply shocks, given the price received by foreign suppliers, an increase in tariff shifts the import demand curve downward and helps trace the foreign export supply curve. Similarly, given the price paid by buyers of imports, a tariff increase shifts the foreign export supply curve upward, which helps identify the import demand curve. Thus, one can identify the demand and supply elasticities simultaneously with the variation in tariffs as an instrument.

To increase the validity of the instrument, we exclude Chinese tariff changes that were due to free-trade agreements or due to regular adjustments (e.g., twice yearly MFN tariff revisions). Accordingly, we use only the changes in Chinese import tariffs against the U.S. products (and decreases in MFN tariffs against non-U.S. products) that were announced in association with the U.S.-China trade war during 2018:1–2019:12, as the variations in the instrument. Specifically, by adding a time subscript ($t$) and taking the log-difference in import demand equation (2.6) and foreign export supply equation (2.9), we may write their estimable equations as:

$$\Delta \ln m_{igt} = \psi_{ig}^{m} + \psi_{st}^{m} - \sigma \Delta \ln p_{igt} + \varepsilon_{igt}^{m}, \tag{2.22}$$

$$\Delta \ln p_{igt}^{*} = \psi_{ig}^{p^*} + \psi_{st}^{p^*} + \omega^* \Delta \ln m_{igt} + \varepsilon_{igt}^{p^*}, \tag{2.23}$$

where $\varpi = \{p^*, m\}$, and $\psi_{ig}^{\varpi}$ and $\psi_{st}^{\varpi}$ are variety and sector-time fixed effects, $\varepsilon_{igt}^{m}$ and $\varepsilon_{igt}^{p^*}$ are the respective import demand and export supply residuals, collecting shocks to import demand $\Delta \ln a_{igt}$ and export supply $\Delta \ln z_{igt}^{*}$, respectively, and other unobservables not controlled for by the fixed effects. Note that in contrast to the U.S., which slapped tariffs against multiple trading partners in selected sectors and also against China in multiple products, China's tariff changes were mainly targeted at the U.S. or uniformly at non-U.S. MFN sources of imports of selected products. This implies limited variations in Chinese tariffs across sources of imports by product. Thus, we have modified the set of fixed effects (FE) controls used in Fajgelbaum et al. (2020). In particular, we drop the product-time ($gt$) FE—as there are limited variations left across $i$ within $gt$ in the case of Chinese import tariffs—and replace the remaining set of FEs ($is$, $it$) with ($ig$, $st$). Thus, we rely on within-variety time variations in tariffs as the source of identification, and use sector-time FEs to control for systematic bias in the sectoral pattern of Chinese trade policies or trade flows across time.

Following the identification strategy described above, we estimate the import demand elasticity $\sigma$ and the foreign (inverse) export supply elasticity $\omega^*$ by instrumenting changes in the duty-inclusive price $\Delta \ln p_{igt}$ and in the import quantity $\Delta \ln m_{igt}$ with variations in the tariff $\Delta \ln(1 + \tau_{igt})$ in equations (2.22) and (2.23), respectively. The estimation results are reported in Table 2.3. Columns (1) to (4) report the reduced-form regressions of different trade outcomes (before-duty import value, import quantity, before-duty unit value and duty-inclusive unit value) on the tariff changes $\Delta \ln(1 + \tau_{igt})$ due to the trade war. Column (5) reports the IV regression estimation of foreign (inverse) export supply elasticity $\hat{\omega}^*$ based on equation (2.23), with its first-stage estimation in Column (2). Column (6) reports the IV regression estimation of import demand elasticity $\hat{\sigma}$ based on equation (2.22), with its first-stage estimation in Column (4).

Columns (1) and (2) show that the import value (before-duty) and quantity respond to tariff changes negatively in very similar magnitudes. The result in Column (3) further indicates that the before-duty unit values do not respond to tariff changes, suggesting a complete pass-through of tariffs to duty-inclusive prices. This is consistent with the result in Column (4), where the duty-inclusive unit value responds to tariffs with elasticity close to one.[3]

The IV estimate of $\omega^*$ in Column (5) is statistically insignificant and numerically negligible. This implies that we cannot reject a horizontal foreign export supply curve, consistent with the finding of a complete pass-through of tariffs in the reduced-form regressions. Column (6) reports the IV estimation of import demand elasticity $\sigma$. It is statistically significant at $\hat{\sigma} = 1.120$ (std. err. = 0.3158). Given these two elasticity estimates, we can calculate the partial (direct) impact on the import value of the targeted varieties. The results are summarized in Table A.1. Specifically, if we consider China's retaliatory tariffs against the U.S. products, the weighted average change in import value of the targeted U.S. products would be:

$$\begin{aligned}\overline{\Delta \ln \left(p_{ig}^* m_{ig}\right)}^{wa} &\equiv \sum_{ig} -\hat{\sigma}\frac{1+\hat{\omega}^*}{1+\hat{\omega}^*\hat{\sigma}}\Delta \ln(1+\tau_{ig}) \cdot \left(p_{ig}^* m_{ig}\right) / \sum_{ig}\left(p_{ig}^* m_{ig}\right) \\ &\equiv \underbrace{-\hat{\sigma}\frac{1+\hat{\omega}^*}{1+\hat{\omega}^*\hat{\sigma}}}_{-1.121}\underbrace{\overline{\Delta \ln(1+\tau_{ig})}^{wa}}_{11.72\%} = -13.14\%,\end{aligned}$$

where the response ratio $-\hat{\sigma}\frac{1+\hat{\omega}^*}{1+\hat{\omega}^*\hat{\sigma}}$ is implied by the variety-level import demand and export supply equations (2.22) and (2.23). The calculations use the elasticity estimates reported in Table 2.3, the pre-war duty-exclusive trade value of 2017 (as weights) and the latest revised tariff change for each variety observed during the period 2018:1–2019:12 (as the shock). Similar calculations suggest that the Chinese MFN tariff cuts ($-3.10\%$ on average across targeted varieties) associated with the tariff war imply a positive direct impact on import values of 3.48%. Together, these imply a combined impact of $-3.64\%$ on Chinese import value in partial equilibrium, based on the relative import values of China from the U.S. and from the non-U.S. MFN sources in 2017. The MFN tariff cuts thus helped cushion the drop in Chinese imports substantially.

[3] Since we measure the duty-inclusive price as the product of duty-exclusive price and the tariff factor: $p_{igt} \equiv p_{igt}^*(1+\tau_{igt})$, the estimate in Column (4), by construction, equals one plus the estimate in Column (3), subject to sample attrition across the two estimations.

### 2.4.2 Demand elasticity across products ($\eta$)

To estimate the demand elasticity $\eta$ across products, we add the time subscript and take the log-difference over time of equation (2.5) such that:

$$\Delta \ln s_{Mgt} = \psi_{st} + (1-\eta)\Delta \ln p_{Mgt} + \varepsilon_{Mgt}, \tag{2.24}$$

where $s_{Mgt} \equiv \frac{p_{Mgt} m_{gt}}{P_{Mst} M_{st}}$ denotes the import share of product $g$ in sector $s$; $\psi_{st}$ is a sector-time fixed-effect term that helps control for the effect of sector-level import price index $-(1-\eta)\Delta \ln P_{Mst}$, among other time-variant sector-level unobservables; and the residual term $\varepsilon_{Mgt}$ absorbs the product-level import demand shock $\Delta \ln a_{Mgt}$ and remaining unobservables.

Note that the import share of each product $s_{Mgt}$ is observed in the data. The product-level import price index is constructed by aggregating the variety-level prices, and taking into account entry and exit of varieties, as in Feenstra (1994):

$$\Delta \ln p_{Mgt} = \frac{1}{1-\sigma} \ln \left( \sum_{i \in \mathscr{C}_{gt}} s_{igt}\, e^{(1-\sigma)\Delta \ln\left(p^*_{igt}(1+\tau_{igt})\right) + \Delta \ln a_{igt}} \right) - \frac{1}{1-\sigma} \ln \left( \frac{S_{g,t}(\mathscr{C}_{gt})}{S_{g,t-1}(\mathscr{C}_{gt})} \right), \tag{2.25}$$

where $\mathscr{C}_{gt}$ is the set of continuing imported varieties of product $g$ between periods $t-1$ and $t$, $s_{igt} \equiv \frac{p_{igt} m_{igt}}{\sum_{i' \in \mathscr{C}_{gt}} p_{i'gt} m_{i'gt}}$ is the share of continuing imported varieties that originate from country $i$ in period $t$, and $S_{g,t}(\mathscr{C}) \equiv \frac{\sum_{i' \in \mathscr{C}} p_{i'gt} m_{i'gt}}{\sum_{i' \in \mathscr{I}_{gt}} p_{i'gt} m_{i'gt}}$ is the share of all imported varieties $\mathscr{I}_{gt}$ of good $g$ at time $t$ accounted for by the varieties in set $\mathscr{C}$. The first term in equation (2.25) corresponds to the conventional price index for the set $\mathscr{C}_{gt}$ of continuing imported varieties. The second term adjusts the price index for the effect of entry and exit of varieties.[4] In the construction of the product-level price index, we use the estimated $\sigma$ and the corresponding residuals (which reflect mean-zero demand shocks $\Delta \ln a_{igt}$) of equation (2.22) from Section 2.4.1.

Applying the same logic as in the estimation of variety-level elasticities $\sigma$ and $\omega^*$, we use product-level tariff changes as the instrument for $\Delta \ln p_{Mgt}$. We construct the IV by the simple average (instead of import-value weighted average) of the tariff

[4] Equation (2.25) can be derived from the product-level import price index $p_{Mg} = \left(\sum_i a_{ig} p_{ig}^{1-\sigma}\right)^{\frac{1}{1-\sigma}}$ and the variety demand equation (2.6).

changes across the continuing imported varieties:[5]

$$\Delta \ln Z_{Mgt} \equiv \ln\left(\frac{1}{N_{gt}^{c}}\sum_{i\in\mathscr{C}_{gt}} e^{\Delta\ln\left(1+\tau_{igt}\right)}\right), \tag{2.26}$$

where $N_{gt}^{c}$ is the number of continuing imported varieties of product $g$ between $t-1$ and $t$.

Table 2.4 reports the estimation results of equation (2.24). Column (1) shows the impact of the instrument on the product-level trade share: higher product-level tariffs lower the import share of the targeted products. This implies that diversion to non-U.S. varieties is less than sufficient to offset the decrease in imports from the U.S. within the same product category. Column (2) provides the first-stage result of the IV regression of (2.24): the sign of the coefficient is positive as expected, since the product-level import price index is aggregated from duty-inclusive variety prices. Column (3) reports the IV estimate of the coefficient of the product-level import demand equation (2.24), which implies an elasticity estimate of $\hat{\eta} = 1.087$. The bootstrapped confidence interval for $\eta$, which accounts for the variance of $\hat{\sigma}$ and the demand shocks from the previous step in Section 2.4.1, is [1.041,1.131].

### 2.4.3 Demand elasticity across domestic and imported bundles ($\kappa$)

We further estimate the top-tier elasticity of substitution, $\kappa$, between the domestic and imported bundles within a sector. Taking the ratio of the expenditures on the imported bundle (2.4) and the domestic bundle (2.3), we have:

$$\Delta\ln\left(\frac{P_{Mst}M_{st}}{P_{Dst}D_{st}}\right) = \psi_s + \psi_t + (1-\kappa)\Delta\ln\left(\frac{P_{Mst}}{P_{Dst}}\right) + \varepsilon_{st}, \tag{2.27}$$

where $\psi_s$ and $\psi_t$ are sector and time fixed effects, used to help control for unobservables across sectors and time, respectively; while the residual $\varepsilon_{st}$ absorbs the remaining relative demand shocks to imported and domestic bundles $\Delta\ln\left(A_{Mst}/A_{Dst}\right)$. The monthly change in the expenditures on domestic goods of sector $s$, $\Delta\ln P_{Dst}D_{st}$, is not observable in the data. We use the difference between the changes in the sectoral production and exports as its proxy. The change in domestic sectoral price index, $\Delta\ln P_{Dst}$, is measured by the change in producer price index (PPI), $\Delta\ln p_{st}$, as implied by the theoretical setup. The change in the sectoral import price index,

[5] As argued by Fajgelbaum et al. (2020), this avoids mechanical correlation of the instrument with the product-level trade share.

$\Delta \ln P_{Mst}$, is constructed from product-level import prices, $\Delta \ln p_{Mgt}$, in a similar manner as in equation (2.25):

$$\Delta \ln P_{Mst} = \frac{1}{1-\eta} \ln \left( \sum_{g \in \mathscr{C}_{st}} s_{gt} \; e^{(1-\eta)\Delta \ln p_{Mgt} + \Delta \ln \left(a_{Mgt}\right)} \right) - \frac{1}{1-\eta} \ln \left( \frac{S_{s,t}\left(\mathscr{C}_{st}\right)}{S_{s,t-1}\left(\mathscr{C}_{st}\right)} \right), \tag{2.28}$$

where $\mathscr{C}_{st}$ is the set of continuing imported products in sector $s$ between periods $t-1$ and $t$, $s_{gt}$ is product $g$'s share in the set of continuing imported products of sector $s$, and $S_{s,t}(\mathscr{C})$ is the share of total import value of sector $s$ at time $t$ accounted for by products in set $\mathscr{C}$.[6] The required inputs, $\eta$ and $\Delta \ln a_{Mgt}$, in (2.28) are based on their counterparts from the product-level estimation of equation (2.24) in Section 2.4.2. The change in relative price of imports $\Delta \ln \frac{P_{Mst}}{P_{Dst}}$ is similarly instrumented by the simple average of tariff changes across the continuing imported products in sector $s$:

$$\Delta \ln Z_{Mst} \equiv \ln \left( \frac{1}{N_{st}^{c}} \sum_{g \in \mathscr{C}_{st}} e^{\Delta \ln Z_{Mgt}} \right), \tag{2.29}$$

where $N_{st}^{c}$ is the number of continuing imported products in sector $s$ between $t-1$ and $t$, and $\Delta \ln Z_{Mgt}$ is the instrument defined in (2.26).

The estimation results are summarized in Table 2.5. Column (1) reports the estimated impact of the average sector-level import tariff changes on the sectoral relative import expenditures. Columns (2) and (3) report the first and second stages of the IV estimation of (2.27), respectively. The estimated coefficients of the two reduced-form specifications in Columns (1) and (2) have the expected signs, but are imprecisely estimated. The IV estimate in Column (3) implies a statistically significant $\hat{\kappa} = 1.173$. The bootstrapped confidence interval for $\hat{\kappa}$, which takes into account the errors in the estimates $\{\hat{\sigma}, \hat{\eta}\}$ and the demand shocks from the previous stages, is [0.541,1.385].

### 2.4.4 Foreign import demand and Chinese export supply elasticities at variety level ($\sigma^*$, $\omega$)

The foreign import demand and Chinese export supply structures at the variety level are estimated based on the same concept as in Section 2.4.1. Taking log

[6] That is, $s_{gt} \equiv \frac{p_{Mgt} m_{gt}}{\sum_{g' \in \mathscr{C}_{st}} p_{Mg't} m_{g't}}$, and $S_{s,t}(\mathscr{C}) \equiv \frac{\sum_{g' \in \mathscr{C}} p_{Mg't} m_{g't}}{\sum_{g' \in \mathscr{G}_{st}} p_{Mg't} m_{g't}}$, where $\mathscr{G}_{st}$ is the set of all products available in sector $s$ at time $t$.

changes of the foreign import demand equation (2.10) across time, we have:

$$\Delta \ln x_{igt} = \psi_{ig}^{x} + \psi_{st}^{x} - \sigma^{*} \Delta \ln \left( \left( 1 + \tau_{igt}^{*} \right) p_{igt}^{X} \right) + \varepsilon_{igt}^{x}, \tag{2.30}$$

where we used $\psi_{ig}^{x}$ and $\psi_{st}^{x}$ to control for potentially unobserved product-destination and sector-time FEs; while the residual $\varepsilon_{igt}^{x}$ absorbs remaining shifts in the foreign demand for Chinese products $\Delta \ln a_{igt}^{*}$. Assume that the export supply of China has a symmetric structure with the foreign export supply, that is, $p_{ig}^{X} = z_{ig} x_{ig}^{\omega}$, where $\omega$ is the inverse export supply elasticity of China and $z_{ig}$ is the product-destination export supply shifter. This implies an estimable equation:

$$\Delta \ln p_{igt}^{X} = \psi_{ig}^{p^X} + \psi_{st}^{p^X} + \omega \Delta \ln x_{igt} + \varepsilon_{igt}^{p^X}, \tag{2.31}$$

where we have included the same set of FE controls as in (2.30); with the residual $\varepsilon_{igt}^{p^X}$ capturing remaining variations in the Chinese export supply shifters $\Delta \ln z_{igt}$, after controlling for the fixed effects. By analogous arguments as in Section 2.4.1, we use the variation in foreign tariffs due to the trade war as the instrument for the independent variables in equations (2.30)–(2.31) to identify $\sigma^{*}$ and $\omega$. For this set of estimations, we use only observations with *ig* corresponding to the U.S. destination, because the U.S. is the only trading partner that raised tariffs against China in this trade war episode. This also limits the set of FEs we can include (product-destination FEs reduced to product FEs) in this case, compared with Fajgelbaum et al. (2020) for the U.S. economy.

Table 2.6 reports the estimation results. The pattern of these estimates is quite similar to those of $\sigma$ and $\omega^{*}$ in Table 2.3: Columns (1) and (2) show that the export value and quantity fell with tariff increases implemented by the U.S., and Columns (3) and (4) imply that Chinese exporters did not change their supply price; the incidence of the U.S. tariff increases was largely borne by the U.S. buyers of imports. Column (5) reports the IV estimation of equation (2.31) with its first stage in Column (2). The estimate ($\hat{\omega} = -0.055$) is statistically insignificant, consistent with the reduced-form result that the U.S. faced a horizontal Chinese export supply curve. Column (6) reports the IV estimation of equation (2.30) with its first stage in Column (4). The result implies that $\hat{\sigma}^{*} = 1.012$ (std. err. = 0.1786), with a bootstrapped confidence interval of [0.161,1.302].

Given the elasticity estimates, we can calculate the partial (direct) impact on the

Chinese export value of targeted products in similar ways as for Chinese imports. In particular, the weighted average change in Chinese export values across targeted products is:

$$\begin{aligned}
\overline{\Delta \ln \left(p_{ig}^{X} x_{ig}\right)}^{wa} &\equiv \sum_{ig} -\hat{\sigma}^{*} \frac{1+\hat{\omega}}{1+\hat{\omega}\hat{\sigma}^{*}} \Delta \ln \left(1+\tau_{ig}^{*}\right) \cdot \left(p_{ig}^{X} x_{ig}\right) / \sum_{ig} \left(p_{ig}^{X} x_{ig}\right) \\
&\equiv \underbrace{-\hat{\sigma}^{*} \frac{1+\hat{\omega}}{1+\hat{\omega}\hat{\sigma}^{*}}}_{-1.0127} \underbrace{\overline{\Delta \ln \left(1+\tau_{ig}^{*}\right)}^{wa}}_{24.18\%} = -24.48\%,
\end{aligned}$$

where the response ratio $-\hat{\sigma}^{*} \frac{1+\hat{\omega}}{1+\hat{\omega}\hat{\sigma}^{*}}$ is implied by the foreign import demand and Chinese export supply equations (2.30) and (2.31). The calculations use the elasticity estimates reported in Table 2.6, the pre-war duty-exclusive trade value of 2017 (as weights), and the latest revised tariff change for each variety observed during the period 2018:1–2019:12 (as the shock). The results are summarized in Table A.1.

### 2.4.5 Pre-trend test

The identification of the import demand and export supply elasticities using tariff changes as the instrument requires the tariff variation to be uncorrelated with the demand and supply shocks. In this section, we conduct pre-trend tests to verify the potential validity of this approach. We show that the tariff changes associated with the trade war (the 18 events listed in Table 2.1) are not systematically correlated with the pre-war trends of the import and export outcomes in terms of values, quantities, before-duty prices and duty-inclusive prices.

Specifically, we compute the average monthly change of these outcome variables during 2017:1–2017:12, and regress them against the latest revised tariff change for each variety during the period of 2018:1–2019:12:

$$\overline{\Delta \ln y_{ig,2017}} = FE + \beta \Delta \ln \left(1+\tau_{ig}\right) + \varepsilon_{ig}. \tag{2.32}$$

The test is conducted for each of the three sets of events—China's retaliatory tariff changes against the U.S., China's tariff cuts on non-U.S. MFN sources of imports, and the U.S. tariff increases against Chinese products. We include suitable sets of fixed effects that are in line with the specifications used for the elasticity estimations in Sections 2.4.1 and 2.4.4, but obviously have to drop the time dimension (*st* to *s*), and also FEs with the country dimension (*i*) when the set of tariff events is targeted at the U.S. or China alone. The results are summarized in Table 2.7.

Panel A1 shows the pre-trend test where we consider China's retaliatory tariff increase against U.S. products. Since all targeted varieties are U.S. products, there are no variations across origins in this case ($ig$ being equivalent to $g$); thus, only fixed effects along the sector ($s$) dimension are controlled for. The results indicate that all pre-war Chinese import outcome variables (with respect to the U.S. as the source of imports) are not systematically correlated with the subsequent tariff increase China imposed against the U.S. products. Panel A2 reports the pre-trend test for China's tariff changes against non-U.S. sources of imports during the trade war. Note that MFN tariff cuts do not apply to all non-U.S. sources of imports (e.g., they are not applicable to FTA trading partners of China). With the extra variations in trade flows and tariffs across trading partners, we control for country-sector ($is$) and product ($g$) fixed effects in this case. We do not observe statistically significant correlations between pre-war Chinese imports from non-U.S. sources and China's subsequent MFN tariff cuts during the trade war. Finally, in Panel B, we conduct the pre-trend test for the U.S. tariff increase against Chinese products. For the same reason as in Panel A1, we include only sector ($s$) fixed effects. The estimated coefficients are insignificant statistically, suggesting that the pre-war export trends of Chinese products are not systematically correlated with subsequent increases in the U.S. tariff against China during the trade war.

### 2.4.6 Dynamic Specification Tests

In this section, we examine whether there exist anticipatory and delayed responses to changes in tariffs during the trade war. This would imply potential downward bias in the elasticity estimates using regressions based on contemporaneous variations in tariffs and trade. To this end, we allow for leads and lags in variety-level reduced-form regressions, controlling for the same set of FEs as in the main estimations:

$$\Delta \ln y_{igt} = \psi_{ig} + \psi_{st} + \sum_{m=-L}^{m=\ell} \beta_m^y [\ln(1+\tau_{ig,t-m}) - \ln(1+\tau_{ig,t-m-1})] + \varepsilon_{igt}, \quad (2.33)$$

where $L$ indicates the maximum leads and $\ell$ the maximum lags (in months) in the response of trade outcome $\Delta \ln y_{igt}$ to the tariff changes. In the following exercise, we set $\ell = L = 6$.

Figure 2.2(A) reports the cumulative estimated coefficients from regression of (2.33) for before-duty import values, quantities, before-duty unit values, and duty-inclusive unit values of Chinese imports at the variety level. There are no significant anticipatory effects in the duty-inclusive unit value and the import quantity, the two key variations used in estimations of $\sigma$ in (2.22) and $\omega^*$ in (2.23), respectively. There also exist no significant delayed effects in the duty-inclusive unit value, as its cumulative effects after the tariff changes remain steady and quantitatively very similar to the contemporaneous effect. This supports the potential validity of the import demand elasticity estimate ($\hat{\sigma}$). Similarly, there exist no quantitatively large delayed effects in the import quantity. Third, the before-duty price does not decline before or after the tariff changes statistically, supporting the conclusion of a complete pass-through at the variety level.

Figure 2.2(B) reports the results for Chinese exports (with respect to the U.S. market, and the U.S. tariffs against Chinese products). The patterns are similar to those for imports overall. We find no evidence of tariff anticipatory/delayed effects on Chinese export quantities, the key variation used in the estimation of export supply elasticity $\omega$ in (2.31). The cumulative responses in the Chinese export quantity mostly reflect its contemporaneous response in the month of tariff changes. On the other hand, there appear to be some irregular anticipatory effects in the before-duty unit value five months before tariff changes; however, instead of declining as theory would suggest, it increases. Overall, there are no significant adjustments in the before-duty unit value over the 12-month horizon. The duty-inclusive unit value, by construct, is equivalent to the before-duty unit value before the month of tariff changes and hence is subject to the same caveat discussed above. Other than that, its cumulative responses upon tariff changes are similar to the contemporaneous impact (in the month of tariff changes) and hence exhibit no delayed effects. Overall, the pattern in the response of the duty-inclusive unit value does not invalidate the use of contemporaneous variations in tariffs and duty-inclusive unit values for the estimation of foreign demand elasticity $\sigma^*$ in (2.30). In view of the caveat observed above, one may choose to adopt a more cautious approach and use the counterpart estimate (2.53) of the U.S. import demand elasticity from the U.S. perspective reported in Fajgelbaum et al. (2020), in place of our estimate (1.012) of the foreign import demand elasticity from the Chinese perspective. This would imply even larger negative welfare effects on Chinese producers of exports (given larger declines in export quantities, and as a result, larger downward adjustment in producer prices in general equilibrium). Thus, we can consider the welfare effects we report below in Section 2.5 (based on our estimate) as plausibly conservative figures.

## 2.5 Welfare Analysis

We now present the general-equilibrium impacts of the trade war on the Chinese economy. Given the tariff shocks, the changes in the endogenous variables are imputed based on first-order approximations of the economic structure set up in Section 2.3 around the pre-war equilibrium in 2017. This choice of first-order approximations (instead of exact hat algebras) is largely driven by the high dimensionality of the current setup (as detailed below).

Specifically, denote $\hat{x} \equiv d\ln x$. The system can be written in terms of the change in each endogenous variable $\{\hat{w}_{sr}, \hat{w}_r^T, \hat{w}_r^{NT}, \hat{L}_r^T, \hat{p}_s, \hat{\phi}_s, \hat{P}_s, \hat{P}_{Ms}, \hat{p}_{Mg}, \hat{p}_{ig}, \hat{R}, \hat{E}_s, \hat{X}, \hat{Y}, \widehat{P_sI_s}, \widehat{p_sQ_s}, \hat{X}_r\}$, given shocks to Chinese and foreign tariffs, $\{d\tau_{ig}, d\tau_{ig}^*\}$, as a result of first-order approximations. The characterization of the system of equations is provided in Appendix 2.6. The numerical implementation is carried out by solving the linear system (A.1)–(A.4), (A.7)–(A.11), (A.14), (A.18)–(A.23), and (A.24) in the reduced form of $\hat{x} = A^{-1}y$, where $\hat{x}$ is a column vector consisting of changes in the endogenous variables, $y$ is a column vector with functions of the given tariff shocks, and $A$ collects the parameters of the economic structure. These include: $i$) demand-side Cobb-Douglas allocation shares ($\beta_s, \beta_{NT}$) for 39 tradable sectors and 1 non-tradable sector, and CES demand elasticities ($\sigma$, $\eta$, $\kappa$) across varieties, products and domestic/imported bundles; $ii$) supply-side Cobb-Douglas input shares ($\alpha_{Ls}, \alpha_{Is}, \alpha_s^{s'}$) of labor and intermediates; $iii$) distributions of sales and employment across sectors and 31 provinces; $iv$) imports and exports across varieties from and to 119 trading partners; and $v$) variety-level foreign demand ($\sigma^*$) and supply ($\omega^*$) elasticities.

We use the 2017 Chinese input-output (IO) tables, China Labor Statistical Yearbook of 2017, and the Chinese customs data for 2017, as documented in Appendix 2.6, to parameterize the allocation shares. For the elasticities, we adopt their estimates from Section 2.4, and set them to zero for statistically insignificant estimates (i.e., $\omega^* = 0$). The shocks to the Chinese and U.S. tariffs, $\{d\tau_{ig}, d\tau_{ig}^*\}$, are measured by the latest revised tariff change for each variety observed during the period 2018:1–2019:12. As a result, we match the model to 2017 data on Chinese economic activities for 31 provinces, 39 tradable sectors (at the level of GB/T-2 digit codes), 1 non-tradable sector, 119 trading partners, 5,362 imported HS-8 products, 122,482 imported varieties (unique product-country-origins), 5,432 exported products, and 374,213 unique product-export-destinations.[7] In sum, the vector $\hat{x}$ includes 663,248 endogenous variables, where 656,166 of them correspond to the variety prices $\hat{p}_{ig}$.[8] Further details about the implementation are provided in Appendix 2.6.

### 2.5.1 Aggregate Effects

Given the tariff shocks to the pre-war equilibrium in 2017, and the changes in the endogenous variables calculated from the system described above, the welfare impact for each primary factor (capital and labor) can be measured as the change in income at initial prices (before the tariff war) that would have left that factor indifferent to the changes in tariffs that took place. Adding up the equivalent variations across all primary factors (capital and labor in each province) gives the aggregate equivalent variation $EV$, or change in aggregate real income. This term can be rewritten as the change in income due to the cost difference in attaining the initial utility level given the price changes (following Dixit and Norman 1980):

$$EV = \underbrace{\sum_s \sum_{g\in\mathcal{G}_s} \sum_{i\in\mathcal{I}_g} x_{ig}\Delta p_{ig}^X}_{EV^X} \underbrace{-\sum_s \sum_{g\in\mathcal{G}_s} \sum_{i\in\mathcal{I}_g} m_{ig}\Delta p_{ig}}_{EV^M} + \Delta R, \qquad (2.34)$$

where $EV^X$ is the increase in the value of the pre-war export basket, $EV^M$ is the drop in income due to increase in the duty-inclusive cost of the pre-war import basket, and $\Delta R$ is the change in tariff revenue.

Table 2.8 reports the decomposition by $EV^X$, $EV^M$, and tariff revenue ($\Delta R$) in Columns (1)–(3) and the aggregate impacts in Column (4). The top panel reports the effects from the 2018–2019 trade war. The bottom two panels study two alter-

[7] The count is based on observations with positive trade value before the trade war.

[8] The count is based on a balanced panel of country-by-product, considering all the trading partners and products observed before and after the war in imports (and exports, respectively).

native hypothetical scenarios, where China retaliated against the U.S. but did not implement MFN tariff cuts, and where China did not retaliate against the U.S. or implement MFN tariff cuts. Each panel reports the monetary equivalent on an annual basis at 2017 prices in billions of US dollars, and the numbers relative to 2017 GDP of China.

The first column shows a decrease of $EV^X$ of \$32.968 billion (0.272% of China's GDP) due to the trade war. This aggregate number equals a model-implied 2.510% decrease in the export price index times a 10.821% observed share of exports of agricultural and industrial sectors in GDP. This implies that the diversion of demand away from China's products (due to higher U.S. tariffs against China and due to China's lower MFN tariffs on non-U.S. sources of imports) dominates potential reallocation toward Chinese products (in response to China's higher tariffs against U.S. products). The drop in the export price indices and the decrease of $EV^X$ would have been less, at \$29.899 billion (0.246% of GDP) if China had not lowered its MFN tariffs on non-U.S. sources of imports during the trade war. On the other hand, the decrease in the export price index would have been more severe if China had not retaliated against the U.S. (and had not changed its MFN tariffs accordingly). This scenario corresponds to a decrease of $EV^X$ of \$37.254 billion (0.307% of GDP).

The next column shows that Chinese buyers of imports sustained an aggregate loss of \$6.906 billion (0.057% of GDP) because of the trade war. The loss would have been larger at \$11.002 billion (0.091% of GDP) if the Chinese government had not lowered MFN tariffs on non-U.S. sources of imports when it increased tariffs against U.S. products. The loss of buyers of imports, on the other hand, would have been negligible and statistically insignificant at \$0.000 billion (0.000% of GDP) if China had not counter-responded to the U.S. tariff hike. This is consistent with a horizontal foreign supply elasticity $\omega^*$, so import price changes that consumers face reflect mainly import tariff changes, which in the last scenario are nil.

The final component of the decomposition implies an increase in tariff revenue of \$1.976 billion (0.016% of GDP). The tariff revenue increase would have approximately tripled at \$5.728 (0.047% of GDP)—with the increase in tariffs against the U.S.—if China had not also lowered MFN tariffs. In the third scenario, without counter-retaliation by China, the tariff revenue is shown to decrease, reflecting a decrease in import volume due to general equilibrium effects of U.S. tariffs on the Chinese economy.

In sum, these numbers imply large negative consequences of the trade war on both Chinese producers and consumers, dominating the positive tariff revenue increase. The loss of the producers (exporters) is more than four times the loss of the buyers of imports. Column (4) suggests an aggregate loss of \$37.898 billion, or 0.312% of China's GDP, as a result of the trade war. Without the counter-retaliation, the loss would have been much larger, at \$38.921 billion (0.321% of GDP), and mostly borne by producers (exporters). The retaliation against the U.S. imports shifted the burden to the Chinese buyers of imports (as seen in the transition from the third to the second scenario). With further adjustment in the MFN tariff rates on non-U.S. sources of imports, this lessened the loss of Chinese buyers of imports and shifted part of the burden back to the producers. Overall, the aggregate loss in $EV$ is significant statistically, except in the second scenario.

### 2.5.2 Regional Effects

We now report the distributional impacts of the trade war across Chinese provinces, from workers' versus all primary factors' perspectives. Chinese import tariffs could negatively affect primary factor owners as consumers of imports. They could also lower the nominal return to primary factors, as the costs of intermediate inputs increase with the import tariffs. The costs of intermediate inputs could increase more in provinces whose production is more concentrated in sectors that use proportionally more inputs targeted by Chinese tariff increases. Simultaneously, the nominal return to primary factors could be negatively affected to larger extents in regions whose production is more concentrated in sectors targeted by the U.S. tariffs (through changes in the producer and export prices), less protected by China's retaliatory tariffs against the U.S., or subject to China's MFN tariff reductions.

Figure 2.3 illustrates the variation in exposure to the trade war across provinces in China: (A) due to China's tariff increases on U.S. products; (B) due to China's MFN tariff cuts; (C) due to the combination of the first two; and (D) due to the U.S. tariff increases on Chinese products. We construct the province-level exposure to tariff shocks by: *i*) computing the trade-weighted tariff changes of each GB/T-2 sector across varieties within the sector, using the 2017 trade shares; and *ii*) computing the wage-bill-weighted tariff changes for each province given the province's employment structure across sectors.[9]

Figure 2.3 suggests that China tended to: (A) retaliate against the U.S. in sectors with a relatively high concentration in the outlying provinces such as Xinjiang, Hainan, and Heilongjiang; and (B) reduce MFN tariffs on sectors concentrated in provinces closer to the coast such as Shanghai and Beijing. Overall, China's tariff increases tended to be biased toward inland provinces and turn negative in the Eastern provinces. Added to the burden, Panel (D) suggests that these provinces also faced higher tariff increases on their exports to the U.S.

Figure 2.4 shows the effects of the trade war on real wages across provinces. The first map (A) shows the province-level reduction in real wages in tradable sectors due to the trade war, and the second map (B) shows real wage losses in the hypothetical scenario where China had not reduced MFN tariffs. Every province experienced a reduction in the tradable real wage. Provinces with larger relative losses are concentrated in the Southeast, whose employment structures were hit more strongly by the U.S. tariff increase. Map (B) suggests that the real wage losses would have been one level higher without the MFN tariff cuts by China. This contrasts with the finding in Table 2.8, where the MFN tariff cuts by China worsened the aggregate loss. This implies that the MFN tariff cuts helped cushion the impacts on workers/consumers via lower import prices, at the cost of producers (and the owners of capital and fixed structures), who faced steeper competition in the product market.

Overall, on average across provinces, the nominal wages for workers in tradable sectors decreased by 3.19% (std. dev. = 0.08%). These income losses were, however, cushioned by a reduced cost of living, as the CPI of tradable goods decreased by 2.34% on average across sectors, reflecting an average 0.53% increase in import prices and 2.69% decrease in prices of domestic goods. As a result, real wages in the tradable sector fell by 0.32% (std. dev. = 0.04%).

Figure 2.5 sums up the total real expenditures of both capital owners and work-

[9] The exposure of region $r$ to the Chinese import tariff changes is $\Delta\tau_r = \sum_{s\in S}\left(\frac{w_{sr}L_{sr}}{w_{Tr}L_r^T}\right)\frac{\sum_{g\in G_s}\sum_{i\in\mathscr{I}_g} p_{ig}^{*} m_{ig}\Delta\tau_{ig}}{\sum_{g'\in G_s}\sum_{i'\in\mathscr{I}_{g'}} p_{i'g'}^{*} m_{i'g'}}$, and the exposure to the U.S. tariff changes is $\Delta\tau_r^{*} = \sum_{s\in S}\left(\frac{w_{sr}L_{sr}}{w_{Tr}L_r^T}\right)\frac{\sum_{g\in G_s}\sum_{i\in\mathscr{I}_g} p_{ig}^{X} x_{ig}\Delta\tau_{ig}^{*}}{\sum_{g'\in G_s}\sum_{i'\in\mathscr{I}_{g'}} p_{i'g'}^{X} x_{i'g'}}$, where $w_r^T L_r^T$ are total tradable wages in province $r$.

ers (i.e., profits and wage incomes in addition to tariff revenue transfer) for each province, and reports their simulated responses to the tariff war, with and without the MFN tariff cuts. The impacts of the full trade war are similar in percentage terms of real wages or real expenditures, as seen in Panel (A) of Figures 2.4 and 2.5. However, the large contrast between Panel (B) of Figure 2.4 and that of Figure 2.5 echoes the re-distributional effects of MFN tariff cuts from the producers of exports ($EV^X$) to the buyers of imports ($EV^M$), as highlighted in Section 2.5.1. The losses in real expenditures across provinces are mitigated while the losses in real wages are aggravated, without the MFN tariff cuts. Thus, the MFN tariff cuts in a way are used by the Chinese government to redistribute real incomes from capital owners to workers, at a greater cost to the aggregate welfare.

### 2.5.3 Trade Diversion Effects

In this section, we report the model-implied trade diversion effects of the trade war. Formulas are provided in Appendix 2.6. Table 2.9 summarizes the diversion of Chinese imports and exports due to the trade war. As China increased tariffs on U.S. products and decreased MFN tariffs against the other trading partners, Chinese imports were diverted from U.S. toward non-U.S. sources. The share of imports from the U.S. dropped from 9.15% to 8.21%. Chinese imports were mainly diverted toward countries in Europe and Asia, and in particular, Germany and Japan. Although China reduced imports from all sources due to general-equilibrium effects, the drop was proportionally less with respect to countries in Europe.

On the other hand, facing the U.S. tariff increase, China diverted its exports toward other markets. The share of exports to the U.S. declined from 19.16% to 16.16%. Meanwhile, its exports to destinations other than the U.S. generally increased by around 0.03%. Thus, as a result of the trade war, China tilted its sources of inputs toward countries in Europe and Asia (19.19% to 19.54%; 52.48% to 52.93%), and also relied more on countries in Europe and Asia as its markets (18.89% to 19.59%; 48.68% to 50.48%).

## 2.6 Conclusion

The U.S.-China tariff war escalated in a short span of 24 months during 2018:1–2019:12 before the Phase One Deal was reached in 2019:12. This paper provides an ex post analysis of the micro and macro responses of the Chinese economy to the tariff shocks of that period. This complements the studies by Amiti et al. (2019), Flaaen et al. (2020), Fajgelbaum et al. (2020), and Cavallo et al. (2021) for the U.S. economy.

In the first step, we use monthly variations during 2018:1–2019:12 in Chinese imports and exports of HS-8 digit products by source and destination countries to identify the elasticities of the Chinese economy's import demand and export supply at the product-country (i.e., variety) level. The identification relies on monthly variations in tariff rates that are uncorrelated with the unobserved demand and supply shocks of the corresponding variety. The tariff shocks associated with the tariff war are taken as the ideal instrument given its unprecedented and uncertain nature. The validity of the instrument was verified with pre-trend and dynamic tests. The resulting elasticity estimates provide a first view of the direct effects of the tariff war on Chinese imports and exports at the variety level.

In the second step, the estimated demand structure is embedded in a general equilibrium model with a supply-side structure calibrated to the Chinese economy. In particular, goods markets (for final demand and intermediate use) are integrated across Chinese provinces but primary inputs (labor and fixed structures) are confined to their current sector-province of employment in the short run. The effects of the tariff shocks on the demand for Chinese and foreign varieties aggregate up via the 3-tier demand system in China, and influence the Chinese producer prices across sectors and the real wages across sector-provinces. The exposure of a sector-province to the tariff war depends on a sector's exposure to the tariff shocks and a province's production structure across sectors.

The tariff war imposed a large welfare loss on Chinese producers/exporters (US$ 32.968 billion) and on buyers of imports (US$ 6.906 billion), with a net loss of aggregate welfare (US$ 37.898 billion) after taking into account the higher tariff revenue. The Chinese initiative to lower MFN tariffs as it raised tariffs against the U.S.

products led to larger aggregate welfare losses at the cost of producers, but appeared to be an effective redistributive policy to cushion the impacts on consumers/workers. The loss of consumers/buyers of imports would have been higher (US$ 11.002 billion) and the average real wage in tradable sectors would have dropped by more (0.38% vs. 0.32%) if not for the MFN tariff cuts. The analysis also indicates that the provinces that are closer to the coast were hit harder (in terms of real wages in tradable sectors or real expenditures) by the tariff war. This occurred not only because these provinces were proportionally more specialized in products targeted by the U.S. tariff hike, but also because the Chinese government tended to lower MFN tariffs on products produced by these provinces. Finally, due to the tariff war, the Chinese economy reduced its share of imports from the U.S. (from 9.15% to 8.21%). At the same time, the share of its exports to the U.S. market dropped from 19.16% to 16.16%. Trade tended to be diverted toward countries in Europe and Asia (as sources of imports and as markets for exports).

Some comments are in order. First, similarly to Fajgelbaum et al. (2020), our estimates suggest horizontal foreign export supply and Chinese export supply curves at the variety level. Hence, the incidence of import tariffs is borne entirely by the importing country at the variety level (although foreign tariffs on Chinese exports can still affect Chinese producer/export prices through general equilibrium adjustments in the Chinese economy). This implies less policy room for China to retaliate for terms-of-trade gains, and might help explain the moderate increase in Chinese tariff rates for a majority of products included in its targeted list, and its move to lower MFN tariffs. Second, a potential caveat to the above finding is the nature of estimation specification, where sector-time fixed effects are controlled for. This is likely to reduce the magnitude of elasticity estimates, if the sector-time fixed effects used to control for unobservables also absorb a significant source of variations in variety-level imports/exports. Third, the general equilibrium structure used has a high resolution with respect to modeling of product/labor markets for the local economy and their supply response. The setup, however, has a very simple structure for the rest of the world (with only supply and demand responses specified at the variety level), and cannot accommodate general equilibrium adjustments in foreign countries or across countries. For example, it cannot address the repercussion of the trade war on the regional or global value chain in which China plays a critical role. Fourth, the model used is static in nature, and thus cannot address potential impacts in the long run due to factor reallocations across regions within the country. We leave these generalizations to future research.

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# A Data Appendix

## A.1 Definitions

Products, varieties and sectors are defined as follows in the analysis:

- Products are defined at the Harmonized System 8-digit level (denoted as HS-8). For example, the HS 8-digit code 40131000 covers the product "inner tubes of rubber used on motor cars."

- Varieties are defined at the product-country level. For example, imports (exports) of "inner tubes of rubber used on motor cars" from (to) the U.S. are a distinct variety.

- Sectors are defined according to the China Industry Classification system (GB/T 4754) at the 2-digit level (denoted as GB/T-2). For example, the GB/T-2 code 29 covers "manufacture of rubber and plastics products."

## A.2 Variety-level Data on Trade and Tariffs

### A.2.1 Trade Data

We obtain China's trade data in monthly frequency for the period 2017:1–2019:12 from the General Administration of Customs, China.[10] We observe the Chinese imports and exports at the HS-8 digit level by the source of imports and the destination of exports (i.e., at the variety level). For each variety, the customs data report the quantities of imports and exports, the value of imports at the CIF price, and the value of exports at the FOB price. The import and export values are reported in current US$ values.

### A.2.2 Tariff Data

Our tariff data comprise two main components, the baseline tariff rates applied to Chinese imports and exports, and tariff changes associated with the U.S.-China trade war. For the Chinese baseline tariff rates, we downloaded the annual tariff schedule of China from the UN TRAINS database via the World Integrated Trade

[10] `http://www.customs.gov.cn/`.

Solution (WITS).[11] Given the tariff rates available at the HS-10 level, we assume that the most-favored-nation (MFN) rate is applied to imports from WTO members, the preferential rate is applied to trading partners with which China has any preferential trade agreement (PTA) in place, and the general duty rate (GDR) is applied to the rest of the world. We then take the simple average of the HS-10 level tariff rates as the HS-8 level tariff rate. This aggregation is due to the fact that the tariff rate changes (or tariff rates in general) published by the Chinese Ministry of Finance are only available at the HS-8 level.[12] We cross-check, correct and supplement the missing values of the data obtained from TRAINS with the annual tariff schedules released by the Ministry of Finance. After constructing the baseline import tariff rate for January 2017, we then update the rates in monthly frequency, given the official announcement by the Ministry of Finance of any tariff changes (tariff increases against the U.S. or MFN tariff cuts against the other WTO members).[13] These tariff changes are specified at the HS-8 level.[14]

For tariffs faced by Chinese exports, we compile the annual tariff rates imposed by Chinese trading partners from the UN TRAINS database.[15] In particular, we use the simple average of Effectively Applied (AHS) tariff rates by Chinese trading partners against China. These are available at the HS-6 digit level. For tariff changes associated with the trade war, we obtain that part of information from Fajgelbaum et al. (2019) (for tariff changes in 2018) and the Office of the United States Trade Representative (USTR)[16] (for tariff changes in 2019). The tariff changes are aggregated from the HS-10 to the HS-6 level based on simple average. The use of the HS-6 digit for tariffs faced by Chinese exports is because the HS codes are

[11] http://wits.worldbank.org/WITS/WITS/QuickQuery/Tariff-ViewAndExportRawData/TariffViewAndExportRawData.aspx?Page=TariffViewAndExportRawData.

[12] http://gss.mof.gov.cn/zhengwuxinxi/zhengcefabu/index_3.html.

[13] http://gss.mof.gov.cn/zhengwuxinxi/zhengcefabu/index_3.html.

[14] Beside the tariff changes associated with the trade war, in constructing the applied tariff rates we also record other tariff revisions. These include annual MFN rate adjustments (normally twice a year, in January and July), tariff reductions resulting from longstanding treaty commitments, new PTAs signed between China and its trading partners, or the removal of import tariff barriers for certain products due to its 13th Five-Year Plan for National Economic and Social Development. These other tariff revisions are used to construct a more precise measure of the applied tariff rate. Their variations, however, are not used in the construction of the instrumental variables, i.e., not used as the source of identification of the elasticities.

[15] http://wits.worldbank.org/WITS/WITS/AdvanceQuery/TariffAndTradeAnalysis/AdvancedQueryDefinition.aspx?Page=TariffandTradeAnalysis.

[16] https://ustr.gov/.

only harmonized across countries up to the level of HS-6 codes. The estimations of trade elasticities for Chinese exports are nonetheless conducted at the HS-8 level of trade (with the HS-6 tariffs assigned to all HS-8 products in the category). Thus, the same caveat noted by Fajgelbaum et al. (2020) applies, that we may overestimate the value of Chinese exports subject to tariffs and underestimate the foreign import demand elasticity.

Following Fajgelbaum et al. (2020), we scale tariff increases by the number of days of the month they were in effect. For example, a 15 p.p. tariff increase enacted on the 20th day of a 30-day month is assigned a 5 p.p. tariff increase (15 * 10/30 = 5) in the initial month, and an additional 10 p.p. increase in the subsequent month.

### A.3 Sector-level Data

We classify sectors using the China Industry Classification system (GB/T 4754), which is widely used in the collection of official statistics on companies and organizations throughout Mainland China. The sector-level data at the GB/T 2-digit level (denoted GB/T-2) are obtained from China's National Bureau of Statistics.[17] The classification includes 97 sectors in total, and 43 sectors in agriculture, mining and manufacturing.

1. Measure of $\triangle \ln P_{Dst}$: The change in the price index of domestically produced goods is proxied by the change in the producer price index. The producer price index for industrial products (PPI) is available with monthly frequency for 40 industrial sectors.

2. Measure of $\triangle \ln(P_{Dst} D_{st})$: The monthly change in expenditures on domestically produced goods is measured as the difference between the changes in sectoral production and exports. The data on the sectoral output (quantity) are available with monthly frequency but only for major products in 27 manufacturing sectors. We normalize the output of each product relative to 2016:1, and use the simple average across products within each sector as the sectoral production index.[18] The export quantity is constructed as the ratio of export

[17] http://www.stats.gov.cn/.

[18] The methodology of constructing the production index usually requires the industrial value-added of each product to be used as the weight in calculating the index, but such data are not available. Thus, in our calculation, we take the weight to be equal across the major products.

values and the producer price index. The estimations of the elasticity $\kappa$ are thus based on a subset of industrial sectors where the above data are available.

3. The input-output (IO) tables are compiled for 2017. These tables quantify annual inputs and outputs of commodities by intermediate and final users in 2017, for 88 sectors.

For the analysis in the paper, we classify GB/T-2 sectors as tradable if they are matched to an HS-6 code in the trade data. For the cross-walk between GB/T sectors and HS products, we use the conversion table of Sheng (2002) (available for 36 industrial sectors), and the concordance tables from WITS (ISIC-HS)[19] and from China's National Bureau of Statistics (ISIC-GB/T)[20] (available for all economic activities). Minor modifications are further made where a product is mapped to more than one sector, using our interpretations of the official descriptions of the products and sectors. There are a total of 39 tradable sectors.

### A.4 Province-level Data

For the general equilibrium analysis, we collect the annual employment and wage data at the sector and province level from the China Labor Statistical Yearbook of 2017. It records the employment and total wages of urban units by sector and region. These are available for 31 provinces and 94 GB/T-2 sectors (covering services, agriculture, mining and manufacturing sectors). All of the 39 tradable sectors are covered individually in both the IO tables and the labor statistics dataset. We aggregate the remaining sectors as a single non-tradable sector, thus reconciling the IO tables and the labor statistics dataset.

[19] `https://192.86.102.134/product_concordance.html`.

[20] `http://www.stats.gov.cn/tjsj/tjbz/hyflbz/201710/t20171012_1541679.html`.

# B Appendix to Section 2.5 (Welfare Analysis)

The general-equilibrium (GE) system follows that of Fajgelbaum et al. (2020). We provide its full derivations in Section 2.6 for ease of reference (correcting some typos of the original paper along the way), and document its implementations in the context of China in Section 2.6. Section 2.6 describes how we evaluate the trade diversion impact given shocks to the system.

## B.1 General Equilibrium System of Changes

The model solution is derived as a system of first-order approximations around an initial equilibrium corresponding to the period before the trade war. Every market-clearing condition is expressed in log-changes. The outcome depends on endogenous variables, observed initial shares, elasticities and tariff shocks. Letting $\hat{x} \equiv d\ln x$, the system describes the log-change of each endogenous variable given shocks to Chinese and foreign tariffs, $\{d\tau_{ig}, d\tau_{ig}^{*}\}$. Using market-clearing conditions, the solution of the model can be expressed as a system for the changes in wages per efficiency unit $\{\hat{w}_{sr}\}$, average wages in the tradable sectors $\{\hat{w}_r^T\}$, wages in the non-tradable sector $\{\hat{w}_r^{NT}\}$, employment in the tradable sector $\{\hat{L}_r^T\}$, producer prices $\{\hat{p}_s\}$, intermediate input prices $\{\hat{\phi}_s\}$, sector price indices $\{\hat{P}_s\}$, sector-level import price indices $\{\hat{P}_{Ms}\}$, product-level import price indices $\{\hat{p}_{Mg}\}$, duty-inclusive prices of imported varieties $\{\hat{p}_{ig}\}$, tariff revenues $\hat{R}$, sector-level expenditures $\{\hat{E}_s\}$, national final consumer expenditures $\hat{X}$, national value added $\hat{Y}$, national intermediate expenditures by sector $\{\widehat{P_s I_s}\}$, national sales by sector $\{\widehat{p_s Q_s}\}$, and final consumer expenditures by region $\{\hat{X}_r\}$.

### B.1.1 Wages, Producer Prices, Input Prices, and Tradable Employment

The first set of equations characterizes $\{\hat{w}_{sr}, \hat{w}_r^T, \hat{w}_r^{NT}, \hat{L}_r^T, \hat{p}_s, \hat{\phi}_s\}$, given $\{\hat{X}_r, \hat{E}_s, \hat{P}_s, \hat{\tau}_{ig}^{*}\}$. First, by (2.19), we have:

$$\hat{w}_{sr} = \frac{1}{1-\alpha_{Is}}\left(\hat{p}_s - \alpha_{Is}\hat{\phi}_s - \alpha_{Ks}\hat{L}_{sr}\right).$$

Define $\chi^I$ as an indicator that equals one if labor is immobile across sectors and zero otherwise. In the case where $\chi^I = 1$, it follows that:

$$\begin{aligned}
\hat{L}_{sr} &= 0, \\
\hat{w}_{sr} &= \frac{1}{1-\alpha_{Is}} \left(\hat{p}_s - \alpha_{Is}\hat{\phi}_s\right), \\
\hat{w}_r^T &\equiv \frac{dw_r^T}{w_r^T} = \frac{\sum_{s\in S} dw_{sr}L_{sr}}{\sum_{s\in S} w_{sr}L_{sr}} = \sum_{s\in S} \frac{w_{sr}L_{sr}}{w_r^T L_r^T}\frac{dw_{sr}}{w_{sr}} = \sum_{s\in\mathscr{S}} \left(\frac{w_{sr}L_{sr}}{w_r^T L_r^T}\right) \frac{\hat{p}_s - \alpha_{Is}\hat{\phi}_s}{1-\alpha_{Is}}.
\end{aligned}$$

In the alternative case where $\chi^I = 0$, we have instead:

$$\begin{aligned}
w_{sr} &= w_r^T, \\
\hat{w}_{sr} &= \hat{w}_r^T = \frac{1}{1-\alpha_{Is}} \left(\hat{p}_s - \alpha_{Is}\hat{\phi}_s - \alpha_{Ks}\hat{L}_{sr}\right), \\
\hat{w}_r^T &\equiv \frac{dw_r^T}{w_r^T} = \sum_{s\in S} \frac{w_{sr}L_{sr}}{w_r^T L_r^T}\left(\frac{dw_{sr}}{w_{sr}} + \frac{dL_{sr}}{L_{sr}} - \frac{dL_r^T}{L_r^T}\right), \\
\hat{L}_r^T &\equiv \frac{dL_r^T}{L_r^T} = \frac{\sum_{s\in S} dL_{sr}}{L_r^T} = \sum_{s\in S} \frac{L_{sr}}{L_r^T}\frac{dL_{sr}}{L_{sr}}.
\end{aligned}$$

Thus, it follows that:

$$\begin{aligned}
\hat{w}_r^T &= \sum_{s\in S} \frac{w_{sr}L_{sr}}{w_r^T L_r^T}\left(\hat{w}_{sr} + \hat{L}_{sr} - \hat{L}_r^T\right) \\
&= \sum_{s\in S} \frac{w_{sr}L_{sr}}{w_r^T L_r^T}\hat{w}_{sr} + \sum_{s\in S} \frac{L_{sr}}{L_r^T}\hat{L}_{sr} - \hat{L}_r^T \\
&= \sum_{s\in S} \frac{w_{sr}L_{sr}}{w_r^T L_r^T}\hat{w}_{sr} \\
\sum_{s\in S}\left(\frac{w_{sr}L_{sr}}{w_r^T L_r^T}\right)\frac{1-\alpha_{Is}}{\alpha_{Ks}}\hat{w}_r^T &= \sum_{s\in S}\left(\frac{w_{sr}L_{sr}}{w_r^T L_r^T}\right)\frac{1}{\alpha_{Ks}}\left(\hat{p}_s - \alpha_{Is}\hat{\phi}_s - \alpha_{Ks}\hat{L}_{sr}\right) \\
\sum_{s\in S}\left(\frac{w_{sr}L_{sr}}{w_r^T L_r^T}\right)\frac{1-\alpha_{Is}}{\alpha_{Ks}}\hat{w}_r^T &= \sum_{s\in S}\left(\frac{w_{sr}L_{sr}}{w_r^T L_r^T}\right)\frac{\hat{p}_s - \alpha_{Is}\hat{\phi}_s}{\alpha_{Ks}} - \hat{L}_r^T.
\end{aligned}$$

In sum, we have:

$$\hat{w}_{sr} = \chi^I \frac{\hat{p}_s - \alpha_{Is}\hat{\phi}_s}{1-\alpha_{Is}} + \left(1-\chi^I\right)\hat{w}_r^T, \tag{A.1}$$

$$\hat{w}_r^T = \chi^I \sum_{s\in\mathscr{S}}\left(\frac{w_{sr}L_{sr}}{w_r^T L_r^T}\right)\frac{\hat{p}_s - \alpha_{Is}\hat{\phi}_s}{1-\alpha_{Is}} + \left(1-\chi^I\right)\frac{\sum_{s\in S}\left(\frac{w_{sr}L_{sr}}{w_r^T L_r^T}\right)\frac{\hat{p}_s-\alpha_{Is}\hat{\phi}_s}{\alpha_{Ks}} - \hat{L}_r^T}{\sum_{s\in S}\left(\frac{w_{sr}L_{sr}}{w_r^T L_r^T}\right)\frac{1-\alpha_{Is}}{\alpha_{Ks}}} \tag{A.2}$$

Second, by the wage rate for non-tradable sectors (2.21), we have:

$$\hat{w}_r^{NT} = \hat{X}_r - \hat{L}_r^{NT}$$

and by full employment in each region, it follows that:

$$\hat{L}_r^T = -\frac{L_r^{NT}}{L_r^T}\hat{L}_r^{NT}.$$

Thus, in sum:

$$\begin{aligned} \hat{w}_r^{NT} &= \chi^I \hat{X}_r + \left(1-\chi^I\right)\hat{w}_r^T, &\text{(A.3)}\\ \hat{L}_r^T &= \left(1-\chi^I\right)\left(\hat{w}_r^T - \hat{X}_r\right)\frac{L_r^{NT}}{L_r^T}. &\text{(A.4)} \end{aligned}$$

Third, note that by the setup, $p_{Dg} = \frac{p_s}{z_g}$; $p_{ig}^X = \delta_{ig}\, p_{Dg}$; and $P_{Ds} = \left(\sum_{g\in\mathscr{G}_s} a_{Dg} p_{D_g}^{1-\eta}\right)^{\frac{1}{1-\eta}}$ holds. It follows that $\hat{p}_{Dg} = \hat{p}_{ig}^X = \hat{P}_{Ds} = \hat{p}_s$. By (2.16) and (2.17), we have:

$$\begin{aligned} \hat{Q}_s &= \sum_{g\in\mathscr{G}_s}\frac{d_g/z_g}{Q_s}\hat{d}_g + \sum_{g\in\mathscr{G}_s}\sum_{i\in\mathscr{I}_g}\frac{\delta_{ig}x_{ig}/z_g}{Q_s}\hat{x}_{ig},\\ &= \sum_{g\in\mathscr{G}_s}\frac{p_{Dg}d_g}{p_sQ_s}\hat{d}_g + \sum_{g\in\mathscr{G}_s}\sum_{i\in\mathscr{I}_g}\frac{p_{ig}^X x_{ig}}{p_sQ_s}\hat{x}_{ig}. \end{aligned}$$

Further, by equations (2.16)–(2.17), (2.3) and (2.10), we have:

$$\begin{aligned} \hat{d}_g &= \hat{D}_s = \hat{E}_s + (\kappa-1)\hat{P}_s - \kappa\hat{p}_s,\ \ \forall\, g\in\mathscr{G}_s\\ \hat{x}_{ig} &= -\sigma^*\left(\frac{d\tau_{ig}^*}{1+\tau_{ig}^*} + \hat{p}_s\right). \end{aligned}$$

Given that $\sum_{g\in\mathscr{G}_s} p_{Dg}d_g = P_{Ds}D_s$, it follows that:

$$\hat{Q}_s = \frac{P_{Ds}D_s}{p_sQ_s}\left(\hat{E}_s + (\kappa-1)\hat{P}_s - \kappa\hat{p}_s\right) - \sum_{g\in\mathscr{G}_s}\sum_{i\in\mathscr{I}_g}\frac{p_{ig}^X x_{ig}}{p_sQ_s}\sigma^*\left(\frac{d\tau_{ig}^*}{1+\tau_{ig}^*} + \hat{p}_s\right). \quad \text{(A.5)}$$

Further, by (2.15) and (2.14), we have:

$$\begin{aligned} \hat{Q}_s &= \sum_{r\in\mathscr{R}}\frac{Q_{sr}}{Q_s}\hat{Q}_{sr}\\ &= \sum_{r\in\mathscr{R}}\frac{Q_{sr}}{Q_s}\left(\frac{1-\alpha_{Ks}}{\alpha_{Ks}}\hat{p}_s - \frac{\alpha_{Is}}{\alpha_{Ks}}\hat{\phi}_s - \frac{\alpha_{Ls}}{\alpha_{Ks}}\hat{w}_{sr}\right)\\ &= \frac{1-\alpha_{Ks}}{\alpha_{Ks}}\hat{p}_s - \frac{\alpha_{Is}}{\alpha_{Ks}}\hat{\phi}_s - \sum_{r\in\mathscr{R}}\frac{p_sQ_{sr}}{p_sQ_s}\frac{\alpha_{Ls}}{\alpha_{Ks}}\hat{w}_{sr}. &\text{(A.6)} \end{aligned}$$

Finally, combining (A.5) and (A.6) yields:

$$\hat{p}_s = \frac{\frac{P_{Ds}D_s}{p_sQ_s}\left(\hat{E}_s + (\kappa-1)\hat{P}_s\right) + \frac{\alpha_{Is}}{\alpha_{Ks}}\hat{\phi}_s + \sum_{r\in\mathscr{R}}\frac{p_sQ_{sr}}{p_sQ_s}\frac{\alpha_{Ls}}{\alpha_{Ks}}\hat{w}_{sr} - \sigma^*\sum_{g\in G_s}\sum_{i\in\mathscr{I}_g}\frac{p_{ig}^X x_{ig}}{p_sQ_s}\frac{d\tau_{ig}^*}{1+\tau_{ig}^*}}{\frac{1-\alpha_{Ks}}{\alpha_{Ks}} + \frac{P_{Ds}D_s}{p_sQ_s}\kappa + \left(1-\frac{P_{Ds}D_s}{p_sQ_s}\right)\sigma^*}, \quad \text{(A.7)}$$

where by (2.12), the change in the price index of intermediates is:

$$\hat{\phi}_s = \sum_{s' \in \mathscr{S}} \frac{\alpha_s^{s'}}{\alpha_{Is}} \hat{P}_{s'}. \tag{A.8}$$

### B.1.2 Consumer Prices, Import Prices, and Tariff Revenue

The second set of equations characterizes $\{\hat{P}_s, \hat{P}_{Ms}, \hat{p}_{Mg}, \hat{p}_{ig}, \hat{R}\}$ given $\{\hat{E}_s, d\tau_{ig}\}$. First, given that $P_s = \left(A_{Ds} P_{Ds}^{1-\kappa} + A_{Ms} P_{Ms}^{1-\kappa}\right)^{\frac{1}{1-\kappa}}$, the sector price index changes according to a weighted average of producer prices and the import price index:

$$\hat{P}_s = \frac{P_{Ds} D_s}{E_s} \hat{p}_s + \left(1 - \frac{P_{Ds} D_s}{E_s}\right) \hat{P}_{Ms}. \tag{A.9}$$

Next, given that $P_{Ms} = \left(\sum_{g \in \mathscr{G}_s} a_{Mg} p_{M_g}^{1-\eta}\right)^{\frac{1}{1-\eta}}$, the import price index in sector $s$ changes according to:

$$\hat{P}_{Ms} = \sum_{g \in G_s} \left(\frac{p_{Mg} m_g}{P_{Ms} M_s}\right) \hat{p}_{Mg}, \tag{A.10}$$

and by $p_{Mg} = \left(\sum_i a_{ig} p_{ig}^{1-\sigma}\right)^{\frac{1}{1-\sigma}}$, the product-level import price index changes according to:

$$\hat{p}_{Mg} = \sum_{i \in \mathscr{I}_g} \left(\frac{p_{ig} m_{ig}}{p_{Mg} m_g}\right) \hat{p}_{ig}. \tag{A.11}$$

Further, from (2.6), (2.5), and (2.3), we have:

$$\begin{aligned} \hat{m}_{ig} &= \hat{m}_g + \sigma \hat{p}_{Mg} - \sigma \hat{p}_{ig} \\ &= \hat{M}_s + \eta \hat{P}_{Ms} + (\sigma - \eta) \hat{p}_{Mg} - \sigma \hat{p}_{ig} \\ &= \hat{E}_s + (\kappa - 1) \hat{P}_s + (\eta - \kappa) \hat{P}_{Ms} + (\sigma - \eta) \hat{p}_{Mg} - \sigma \hat{p}_{ig}. \end{aligned} \tag{A.12}$$

From the foreign export supply (2.9) and the price relationship (2.7), we also have:

$$\hat{m}_{ig} = \frac{1}{\omega^*} \left(\hat{p}_{ig} - \frac{d\tau_{ig}}{1 + \tau_{ig}}\right). \tag{A.13}$$

Combining (A.12) and (A.13), it follows that:

$$\hat{p}_{ig} = \frac{\omega^*}{1 + \omega^* \sigma} \left(\hat{E}_s + (\kappa - 1)\hat{P}_s + (\eta - \kappa)\hat{P}_{Ms} + (\sigma - \eta)\hat{p}_{Mg}\right) + \frac{1}{1 + \omega^* \sigma} \frac{d\tau_{ig}}{1 + \tau_{ig}}. \tag{A.14}$$

Lastly, recall the definition of tariff revenue,

$$R = \sum_{s \in \mathscr{S}} \sum_{g \in G_s} \sum_{i \in \mathscr{I}_g} \tau_{ig} p_{ig}^* m_{ig}. \tag{A.15}$$

Taking the second-order total differentiation gives:

$$\begin{aligned}
dR &= \sum_s \sum_g \sum_i \left( p^*_{ig} m_{ig} d\tau_{ig} + \tau_{ig} m_{ig} dp^*_{ig} + \tau_{ig} p^*_{ig} dm_{ig} \right) \\
&+ \frac{1}{2} \sum_s \sum_g \sum_i \left( 2 m_{ig} dp^*_{ig} d\tau_{ig} + 2 p^*_{ig} dm_{ig} d\tau_{ig} + 2 \tau_{ig} dp^*_{ig} dm_{ig} \right) \\
&= \sum_s \sum_g \sum_i p^*_{ig} m_{ig} d\tau_{ig} + \sum_s \sum_g \sum_i \tau_{ig} p^*_{ig} m_{ig} \left( \hat{p}^*_{ig} + \hat{m}_{ig} \right) + \sum_s \sum_g \sum_i d\tau_{ig} p^*_{ig} m_{ig} \left( \hat{p}^*_{ig} + \hat{m}_{ig} \right) \\
&+ \frac{1}{2} \sum_s \sum_g \sum_i \tau_{ig} d^2 \left( p^*_{ig} m_{ig} \right).
\end{aligned} \tag{A.16}$$

It follows that:

$$\hat{R} = \sum_s \sum_{g \in G_s} \sum_i \frac{p^*_{ig} m_{ig}}{R} d\tau_{ig} + \sum_s \sum_{g \in G_s} \sum_i \frac{p^*_{ig} m_{ig}}{R} \left( \tau_{ig} + d\tau_{ig} \right) \left( \hat{p}^*_{ig} + \hat{m}_{ig} \right) + \frac{1}{2} \sum_s \sum_{g \in G_s} \sum_i \frac{\tau_{ig}}{R} d^2 \left( p^*_{ig} m_{ig} \right). \tag{A.17}$$

We set the last term $\tau_{ig} d^2 \left( p^*_{ig} m_{ig} \right)$ to 0, provided that the initial tariffs $\tau_{ig}$ are reasonably small. Using the solutions for $\hat{p}_{ig}$ and $\hat{m}_{ig}$ from equations (A.14) and (A.13), in addition to (2.7), we get:

$$\begin{aligned}
\hat{R} &= \sum_s \sum_{g \in G_s} \sum_i \left( \tau_{ig} + d\tau_{ig} \right) \frac{p^*_{ig} m_{ig}}{R} \frac{1 + \omega^*}{1 + \omega^* \sigma} \left( \hat{E}_s + (\kappa - 1) \hat{P}_s + (\eta - \kappa) \hat{P}_{Ms} + (\sigma - \eta) \hat{p}_{Mg} \right) \\
&+ \sum_s \sum_{g \in G_s} \sum_i \left( 1 - \tau_{ig} \frac{\sigma - 1}{1 + \omega^* \sigma} \right) \frac{p^*_{ig} m_{ig}}{R} \frac{d\tau_{ig}}{1 + \tau_{ig}} \\
&- \sum_s \sum_{g \in G_s} \sum_i \frac{p_{ig} m_{ig}}{R} \sigma \frac{1 + \omega^*}{1 + \omega^* \sigma} \left( \frac{d\tau_{ig}}{1 + \tau_{ig}} \right)^2.
\end{aligned} \tag{A.18}$$

### B.1.3 Sector and Region Demand Shifters

The third set of equations characterizes the sector and region level expenditure shifters $\{\hat{E}_s, \hat{X}_r\}$ given $\{\hat{R}, \hat{p}_s, \hat{\phi}_s, \hat{w}^{NT}_r, \hat{w}_{sr}\}$. The expenditure in sector $s$ is defined as $E_s = P_s C_s + P_s I_s$, and from (2.8) we have $P_s C_s = \beta_s X$, where $X$ is the total national expenditure, defined as $X = Y + R + D$, where $D$ is the trade deficit. We assume that the national trade deficit is determined by factors outside the model and remains unchanged. Thus, it follows that:

$$\hat{E}_s \equiv \frac{P_s C_s}{E_s} \hat{X} + \left( 1 - \frac{P_s C_s}{E_s} \right) \widehat{P_s I_s}, \tag{A.19}$$

$$\hat{X} = \frac{Y}{X} \hat{Y} + \frac{R}{X} \hat{R}. \tag{A.20}$$

Since we assume that the non-tradable sectors use only labor as input, this implies that the national income equals $Y = \sum_{r \in \mathscr{R}} P_{NT,r} Q_{NT,r} + \sum_{s \in \mathscr{S}} \left( 1 - \alpha_{Is} \right) p_s Q_s$. Hence,

$$\hat{Y} = \sum_{r\in\mathscr{R}} \left(\frac{P_{NT,r}Q_{NT,r}}{Y}\right)\hat{X}_r + \sum_{s\in\mathscr{S}} (1-\alpha_{Is})\left(\frac{p_sQ_s}{Y}\right)\sum_{r\in\mathscr{R}}\left(\frac{p_sQ_{sr}}{p_sQ_s}\right)\left(\hat{p}_s+\hat{Q}_{sr}\right). \tag{A.21}$$

The total demand for intermediates of sector $s$ is defined as:

$$P_sI_s = \sum_{s'\in\mathscr{S}} \alpha_{s'}^{s} p_{s'}Q_{s'},$$

so that

$$\widehat{P_sI_s} = \sum_{s'\in\mathscr{S}} \alpha_{s'}^{s} \sum_{r\in\mathscr{R}} \frac{p_{s'}Q_{s'r}}{P_sI_s}\left(\hat{p}_{s'}+\hat{Q}_{s'r}\right). \tag{A.22}$$

Using (2.14) for $Q_{sr}$, we have:

$$\hat{p}_s+\hat{Q}_{sr} = \frac{1}{\alpha_{Ks}}\hat{p}_s - \frac{\alpha_{Is}}{\alpha_{Ks}}\hat{\phi}_s - \frac{\alpha_{Ls}}{\alpha_{Ks}}\hat{w}_{sr}. \tag{A.23}$$

By (2.8), we have $P_{NT,r}Q_{NT,r} = \beta_{NT}X_r$. Thus, using (2.18), the change of expenditures in region $r$ can be expressed as:

$$\hat{X}_r = \frac{\sum_{s\in\mathscr{S}} \frac{p_sQ_{sr}}{X_r}(1-\alpha_{Is})\left(\hat{p}_s+\hat{Q}_{sr}\right) + \frac{b_rR}{X_r}\hat{R}}{1-\frac{P_{NT,r}Q_{NT,r}}{X_r}}. \tag{A.24}$$

### B.2 Implementation

We use the 2017 Chinese input-output (IO) tables, China Labor Statistical Yearbook of 2017, and the Chinese customs data for 2017, as documented in Appendix 2.6, to parameterize the allocation shares. We basically follow the same steps as in Fajgelbaum et al. (2020) to construct the shares. Differences in the Chinese context are highlighted below. The share of expenditures on the non-tradable good is set at $\beta_{NT} = 0.6$, such that the model matches the observed 18% share of imports in GDP. Implementing the system also requires information on labor income and employment shares by regions. We allocate the sectoral labor compensation (from the IO tables) across Chinese provinces using the sector-province labor compensation shares (from China Labor Statistical Yearbook of 2017). All 31 provinces have positive employment in both tradable and non-tradable sectors. Finally, for information on import and export flows by variety, we reconcile the sector-level trade flows from the IO tables and the variety-level trade flows from the customs data, by allocating the sector-level import and export flows (from the IO tables) across varieties using the import and export shares at the variety level within each GB/T-2 sector (observed in the Chinese customs data).

### B.3 Trade Diversion Impacts

Note that the change in Chinese imports from a trading partner $i$ across all products in sector $s$ is:

$$\widehat{\sum_{g\in\mathscr{G}_s} p^*_{ig}m_{ig}} = \sum_{g\in\mathscr{G}_s}\left(\frac{p^*_{ig}m_{ig}}{\sum_{g\in\mathscr{G}_s} p^*_{ig}m_g}(\hat{p}^*_{ig}+\hat{m}_{ig})\right), \tag{A.25}$$

and across all tradable sectors is:

$$\sum_{s\in\mathscr{S}}\widehat{\sum_{g\in\mathscr{G}_s} p^*_{ig}m_{ig}} = \sum_{s\in\mathscr{S}}\sum_{g\in\mathscr{G}_s}\left(\frac{p^*_{ig}m_{ig}}{\sum_{s\in\mathscr{S}}\sum_{g\in\mathscr{G}_s} p^*_{ig}m_{ig}}(\hat{p}^*_{ig}+\hat{m}_{ig})\right). \tag{A.26}$$

By aggregating across trading partners within a set of countries $i\in\mathscr{I}_o$, the corresponding expressions are:

$$\sum_{i\in\mathscr{I}_o}\widehat{\sum_{g\in\mathscr{G}_s} p^*_{ig}m_{ig}} = \sum_{i\in\mathscr{I}_o}\sum_{g\in\mathscr{G}_s}\left(\frac{p^*_{ig}m_{ig}}{\sum_{i\in\mathscr{I}_o}\sum_{g\in\mathscr{G}_s} p^*_{ig}m_{ig}}(\hat{p}^*_{ig}+\hat{m}_{ig})\right), \tag{A.27}$$

$$\sum_{s\in\mathscr{S}}\widehat{\sum_{i\in\mathscr{I}_o}\sum_{g\in\mathscr{G}_s} p^*_{ig}m_{ig}} = \sum_{s\in\mathscr{S}}\sum_{i\in\mathscr{I}_o}\sum_{g\in\mathscr{G}_s}\left(\frac{p^*_{ig}m_{ig}}{\sum_{s\in\mathscr{S}}\sum_{i\in\mathscr{I}_o}\sum_{g\in\mathscr{G}_s} p^*_{ig}m_{ig}}(\hat{p}^*_{ig}+\hat{m}_{ig})\right) \tag{A.28}$$

Next, using (2.10), we have:

$$\begin{aligned}
\hat{x}_{ig} &= -\sigma^*\hat{p}^X_{ig} = -\sigma^*\hat{p}_s, && \text{for } i\neq US;\\
\hat{x}_{ig} &= -\sigma^*\left(\frac{d\tau^*_{ig}}{1+\tau^*_{ig}}+\hat{p}_s\right), && \text{for } i = US.
\end{aligned}$$

Thus, for each $s\in S$ and destination $i\neq US$, the change in Chinese exports is:

$$\begin{aligned}
\widehat{EX}_{-US,s} &= \widehat{\sum_{i\neq US}\sum_{g\in\mathscr{G}_s} p^X_{ig}x_{ig}} = \sum_{i\neq US}\sum_{g\in\mathscr{G}_s}\left(\frac{p^X_{ig}x_{ig}}{\sum_{i\neq US}\sum_{g\in\mathscr{G}_s} p^X_{ig}x_{ig}}(\hat{p}^X_{ig}+\hat{x}_{ig})\right)\\
&= \sum_{i\neq US}\sum_{g\in\mathscr{G}_s}\left(\frac{p^X_{ig}x_{ig}}{\sum_{i\neq US}\sum_{g\in\mathscr{G}_s} p^X_{ig}x_{ig}}(1-\sigma^*)\hat{p}_s\right),
\end{aligned} \tag{A.29}$$

and for $i = US$:

$$\begin{aligned}
\widehat{EX}_{US,s} &= \widehat{\sum_{g\in\mathscr{G}_s} p^X_{ig}x_{ig}} = \sum_{g\in\mathscr{G}_s}\left(\frac{p^X_{ig}x_{ig}}{\sum_{g\in\mathscr{G}_s} p^X_{ig}x_{ig}}(\hat{p}^X_{ig}+\hat{x}_{ig})\right)\\
&= \sum_{g\in\mathscr{G}_s}\left(\frac{p^X_{ig}x_{ig}}{\sum_{g\in\mathscr{G}_s} p^X_{ig}x_{ig}}\left((1-\sigma^*)\hat{p}_s-\sigma^*\frac{d\tau^*_{ig}}{1+\tau^*_{ig}}\right)\right).
\end{aligned} \tag{A.30}$$

The change in Chinese exports of all tradable sectors can be similarly aggregated from the sector-level exports.

Table 2.1: Trade War Events during 2018–2019

| Event | Effective Date | Products | Trade Value in 2017 | | Tariff (%) | |
|---|---|---|---|---|---|---|
| | | (# HS-8) | (million US$) | (%) | before | after |
| Panel A. Tariff increase on Chinese products enacted by U.S. | | | | | | |
| 1 | February 7, 2018 | 12 | 983 | 0.04 | 1.11 | 31.11 |
| 2 | March 27, 2018 | 248 | 2,868 | 0.13 | 7.17 | 22.99 |
| 3 | July 6, 2018 | 957 | 59,890 | 2.63 | 1.38 | 26.91 |
| 4 | August 23, 2018 | 345 | 19,810 | 0.87 | 15.39 | 34.60 |
| 5 | September 24, 2018 | 3829 | 189,400 | 8.32 | 7.56 | 14.96 |
| 6 | May 10, 2019 | —”— | —”— | –”– | 14.96 | 29.99 |
| 7 | September 1, 2019 | 1859 | 131,400 | 5.77 | 12.59 | 22.60 |
| Panel B1. China’s retaliatory tariffs on U.S. products | | | | | | |
| 1 | April 2, 2018 | 93 | 2,970 | 0.17 | 11.15 | 27.75 |
| 2 | July 6, 2018 | 267 | 33,830 | 1.98 | 12.81 | 35.56 |
| 3 | August 23, 2018 | 201 | 14,110 | 0.83 | 14.16 | 32.82 |
| 4 | September 24, 2018 | 5190 | 58,160 | 3.41 | 9.91 | 16.43 |
| 5 | January 1, 2019 | 120 | 14,250 | 0.83 | 24.39 | 13.53 |
| 6 | June 1, 2019 | 4545 | 40,220 | 2.35 | 10.3 | 17.13 |
| 7 | September 1, 2019 | 1153 | 28,670 | 1.68 | 9.63 | 18.47 |
| Panel B2. China’s MFN tariff cuts | | | | | | |
| 8 | May 1, 2018 | 26 | 13,710 | 0.8 | 2.12 | 0 |
| 9 | July 1, 2018 | 151 | 59,590 | 3.49 | 11.03 | 7.01 |
| 10 | July 1, 2018 | 1376 | 36,030 | 2.11 | 13.69 | 7.01 |
| 11 | November 1, 2018 | 1532 | 59,610 | 3.49 | 9.57 | 7.95 |

Note: The table reports tariff events implemented by the U.S. (Panel A) and China (Panel B), which are used as sources of identification in the estimations of demand and supply elasticities in Section 2.4. In addition to the retaliation against U.S. products (Panel B1), China also implemented MFN tariff cuts in response (Panel B2). The columns display: the number of HS-8 products affected; the value of trade affected (in million US$); the corresponding shares (%) in 2017; and the simple monthly average tariff rates (in percentage points) across targeted products in the month before and the month after the implementation month (which is taken to be the current month if the implementation date is before the 15th of the month and the next month otherwise). The denominator of trade share is the 2017 annual US$ value of total Chinese exports (imports) in Panel A (Panel B), respectively. See the text for data sources. In Panel A, Event 6 applies to the same set of products as Event 5 but with an upward revision of the tariff rates.

Table 2.2: Sector-Level Tariff Variations

| | | Imports (Chinese tariffs) | | | | Exports (U.S. tariffs) | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | | | Δ Tariffs | | | | Δ Tariffs | |
| Sector | GB/T-2 | # Products | # Varieties | Mean | Std. dev. | # Products | # Varieties | Mean | Std. dev. |
| (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| Agricultural Products | 1-5 | 77 | 121 | 0.15 | 0.10 | 94 | 94 | 0.24 | 0.11 |
| Mining | 6-12 | 126 | 410 | 0.09 | 0.13 | 71 | 71 | 0.21 | 0.07 |
| Processing of Food from Agricultural Products | 13 | 448 | 1687 | 0.07 | 0.21 | 371 | 371 | 0.21 | 0.09 |
| Manufacture of Foods | 14 | 174 | 1564 | -0.01 | 0.15 | 143 | 143 | 0.22 | 0.09 |
| Manufacture of Liquor, Beverages | 15 | 75 | 790 | -0.03 | 0.19 | 74 | 74 | 0.13 | 0.08 |
| Manufacture of Tobacco | 16 | 8 | 43 | 0.10 | 0.14 | 6 | 6 | 0.19 | 0.13 |
| Manufacture of Textiles | 17 | 740 | 13225 | -0.02 | 0.11 | 777 | 777 | 0.20 | 0.08 |
| Manufacture of Wearing Apparel and Accessories | 18 | 160 | 5334 | -0.06 | 0.10 | 158 | 158 | 0.12 | 0.06 |
| Manufacture of Leather Products and Footwear | 19 | 138 | 3320 | -0.04 | 0.10 | 139 | 139 | 0.16 | 0.09 |
| Manufacture of Wood Products | 20 | 126 | 788 | 0.04 | 0.12 | 128 | 128 | 0.21 | 0.09 |
| Manufacture of Furniture | 21 | 31 | 234 | 0.08 | 0.13 | 34 | 34 | 0.25 | 0.04 |
| Manufacture of Paper and Paper Products | 22 | 121 | 2412 | 0.03 | 0.09 | 120 | 120 | 0.24 | 0.05 |
| Printing and Reproduction of Recording Media | 23 | 35 | 796 | 0.03 | 0.09 | 36 | 36 | 0.13 | 0.06 |
| Manufacture of Articles for Culture Activities | 24 | 210 | 4146 | -0.05 | 0.12 | 195 | 195 | 0.15 | 0.08 |
| Processing of Petroleum, Coking | 25 | 41 | 114 | 0.17 | 0.12 | 27 | 27 | 0.23 | 0.05 |
| Manufacture of Raw Chemical Materials | 26 | 903 | 4254 | 0.08 | 0.11 | 876 | 876 | 0.23 | 0.08 |
| Manufacture of Medicines | 27 | 151 | 458 | 0.07 | 0.11 | 55 | 55 | 0.24 | 0.07 |
| Manufacture of Chemical Fibers | 28 | 54 | 54 | 0.17 | 0.08 | 64 | 64 | 0.20 | 0.09 |
| Manufacture of Rubber and Plastics Products | 29 | 154 | 1329 | 0.06 | 0.11 | 156 | 156 | 0.24 | 0.06 |
| Manufacture of Non-metallic Mineral Products | 30 | 232 | 3212 | 0.02 | 0.11 | 240 | 240 | 0.23 | 0.06 |
| Smelting and Pressing of Ferrous Metals | 31 | 223 | 1053 | 0.13 | 0.13 | 239 | 239 | 0.31 | 0.07 |
| Smelting and Pressing of Non-ferrous Metals | 32 | 177 | 400 | 0.15 | 0.09 | 130 | 130 | 0.22 | 0.06 |
| Manufacture of Metal Products | 33 | 299 | 4844 | 0.02 | 0.12 | 293 | 293 | 0.23 | 0.07 |
| Manufacture of General Purpose Machinery | 34 | 470 | 4232 | 0.07 | 0.11 | 509 | 509 | 0.27 | 0.11 |
| Manufacture of Special Purpose Machinery | 35 | 406 | 2123 | 0.08 | 0.12 | 454 | 454 | 0.24 | 0.12 |
| Manufacture of Automobiles | 36 | 180 | 2624 | -0.03 | 0.09 | 160 | 160 | 0.23 | 0.09 |
| Manufacture of Transport Equipment | 37 | 64 | 440 | 0.06 | 0.14 | 101 | 101 | 0.24 | 0.10 |
| Manufacture of Electrical Machinery | 38 | 302 | 4057 | 0.00 | 0.13 | 276 | 276 | 0.29 | 0.12 |
| Manufacture of Computers / Electronic Equipment | 39 | 228 | 656 | 0.06 | 0.15 | 227 | 227 | 0.26 | 0.16 |
| Manufacture of Measuring Instruments/Machinery | 40 | 176 | 1012 | 0.04 | 0.11 | 205 | 205 | 0.28 | 0.15 |
| Other Manufactures | 41 | 57 | 1229 | -0.04 | 0.12 | 40 | 40 | 0.14 | 0.07 |
| Utilization of Waste Resources | 42 | 26 | 55 | 0.23 | 0.10 | 30 | 30 | 0.19 | 0.08 |

Note: The table shows the mean and standard deviation of tariff changes for Chinese imports and exports across 2-digit GB/T sectors. A tariff change of 0.10 indicates a 10 percentage point increase. For imports, China implemented both retaliatory tariff increases against the U.S., and MFN tariff cuts on sources of imports where MFN rates apply. Sectors with the same number of targeted varieties and products in Columns (3) and (4) reflect import tariff increase targeting U.S. products without accompanying decrease in MFN tariffs. For Chinese exports, which faced only U.S. tariff increases, the number of products targeted by trading partners is equal to that of varieties targeted. Due to space constraints, we aggregate sectors of Agricultural products and of Mining.

Table 2.3: Estimation of Variety-level Elasticities—Import Demand ($\sigma$) and Foreign Export Supply ($\omega^*$)

| | $\Delta \ln p^*_{igt} m_{igt}$ (1) | $\Delta \ln m_{igt}$ (2) | $\Delta \ln p^*_{igt}$ (3) | $\Delta \ln p_{igt}$ (4) | $\Delta \ln p^*_{igt}$ (5) | $\Delta \ln m_{igt}$ (6) |
|---|---|---|---|---|---|---|
| $\Delta \ln(1+\tau_{igt})$ | -1.133*** | -1.121*** | 0.009 | 1.004*** | | |
| | (0.2940) | (0.2214) | (0.1740) | (0.1770) | | |
| $\Delta \ln m_{igt}$ | | | | | -0.008 | |
| | | | | | (0.1549) | |
| $\Delta \ln p_{igt}$ | | | | | | -1.120*** |
| | | | | | | (0.3158) |
| Country × Product FE | Y | Y | Y | Y | Y | Y |
| Sector × Time FE | Y | Y | Y | Y | Y | Y |
| 1st-stage $F$ | | | | | 40.179 | 81.805 |
| Bootstrap CI | | | | | [-0.146,0.204] | [0.853,1.432] |
| $R^2$ | 0.038 | 0.027 | 0.035 | 0.027 | 0.012 | 0.192 |
| $N$ | 2,207,210 | 2,129,628 | 2,129,660 | 2,129,138 | 2,129,628 | 2,129,138 |

Note: The table reports the variety-level import responses to import tariffs. Columns (1) to (4) report the reduced-form regression of different trade outcomes (before-duty import value, import quantity, before-duty unit value and duty-inclusive unit value) on the tariff changes. Column (5) reports the IV regression estimation of foreign (inverse) export supply elasticity $\hat{\omega}^*$ based on equation (2.23), with its first-stage estimation in Column (2). Column (6) reports the IV regression estimation of import demand elasticity $\hat{\sigma}$ based on equation (2.22), with its first-stage estimation in Column (4). Robust standard errors (in parentheses) are clustered at the product and country level. 90% bootstrap confidence intervals of ($\hat{\omega}^*$ and $\hat{\sigma}$) were constructed from 1000 samples. The symbols $^*$, $^{**}$, and $^{***}$ indicate statistical significance at the 10%, 5%, and 1% level, respectively. Sample: monthly variety-level import data from 2017:1 to 2019:12.

Table 2.4: Estimation of Product-level Elasticity

| | $\Delta \ln s_{Mgt}$ (1) | $\Delta \ln p_{Mgt}$ (2) | $\Delta \ln s_{Mgt}$ (3) |
|---|---|---|---|
| $\Delta \ln Z_{Mgt}$ | -1.537** | 17.639*** | |
| | (0.6271) | (6.2563) | |
| $\Delta \ln p_{Mgt}$ | | | -0.087*** |
| | | | (0.0230) |
| Sector × Time FE | Y | Y | Y |
| 1st-stage $F$ | | | 19.187 |
| $\hat{\eta}$ (se[$\hat{\eta}$]) | | | 1.087 (0.0230) |
| Bootstrap CI | | | [1.041,1.131] |
| $R^2$ | 0.015 | 0.010 | 0.351 |
| $N$ | 226,372 | 226,372 | 226,372 |

Note: The table reports product-level import responses to import tariffs. Column (1) reports the reduced-form regression of each imported product's share within sectoral imports, $s_{Mgt}$, on the product-level instrument, $Z_{Mgt}$. Column (2) reports the regression of the product-level import price index $p_{Mgt}$ on $Z_{Mgt}$. Column (3) reports the IV estimation of product-level elasticity based on equation (2.24), with its first-stage estimation in Column (2). The product-level import price index is constructed using $\hat{\sigma}$ from Column (6) of Table 2.3 according to equation (2.25), and the instrument is constructed using equation (2.26). Robust standard errors (in parentheses) are clustered at the product level. 90% bootstrap confidence intervals of $\hat{\eta}$ were constructed from 1000 samples. The symbols $^{*}$, $^{**}$, and $^{***}$ indicate statistical significance at the 10%, 5%, and 1% level, respectively. Sample: monthly product-level import data from 2017:1 to 2019:12.

Table 2.5: Estimation of Sector-level Elasticity

| | $\Delta \ln \frac{P_{Mst}M_{st}}{P_{Dst}D_{st}}$ (1) | $\Delta \ln \frac{P_{Mst}}{p_{st}}$ (2) | $\Delta \ln \frac{P_{Mst}M_{st}}{P_{Dst}D_{st}}$ (3) |
|---|---|---|---|
| $\Delta \ln Z_{Mst}$ | -15.055 | 86.888 | |
| | (9.7353) | (201.2985) | |
| $\Delta \frac{P_{Mst}}{p_{st}}$ | | | -0.173 |
| | | | (0.3208) |
| Sector FE | Y | Y | Y |
| Time FE | Y | Y | Y |
| 1st-stage $F$ | | | 0.546 |
| $\hat{\kappa}(se[\hat{\kappa}])$ | | | 1.173 (0.3208) |
| Bootstrap CI | | | [0.541,1.385] |
| $R^2$ | 0.194 | 0.232 | - |
| $N$ | 850 | 850 | 850 |

Note: The table reports sector-level import responses to import tariffs. Column (1) reports the reduced-form regression of the ratio of the expenditure on foreign goods and domestic goods, $\frac{P_{Mst}M_{st}}{P_{Dst}D_{st}}$, on the sector-level instrument, $Z_{Mst}$. Column (2) reports the regression of the ratio of sector-level import price index and domestic price index $\frac{P_{Mst}}{p_{st}}$ on $Z_{Mst}$. Column (3) reports the IV estimation of sector-level elasticity based on equation (2.27), with its first-stage estimation in Column (2). The sector import price index is constructed using $\hat{\sigma}$ from Column (6) of Table 2.3, and $\hat{\eta}$ from Column (3) of Table 2.4, according to equation (2.28), and the instrument is constructed using equation (2.29). Robust standard errors (in parentheses) are clustered at the sector level. 90% bootstrap confidence intervals of $\hat{\kappa}$ were constructed from 1000 samples. The symbols $^{*}$, $^{**}$, and $^{***}$ indicate statistical significance at the 10%, 5%, and 1% level, respectively. Sample: monthly sector-level data from 2017:1 to 2019:12.

Table 2.6: Estimation of Variety-level Elasticities—Foreign Import Demand ($\sigma^*$) and Chinese Export Supply ($\omega$)

| | $\Delta \ln p^X_{igt} x_{igt}$ (1) | $\Delta \ln x_{igt}$ (2) | $\Delta \ln p^X_{igt}$ (3) | $\Delta \ln p^X_{igt}(1+\tau^*_{igt})$ (4) | $\Delta \ln p^X_{igt}$ (5) | $\Delta \ln x_{igt}$ (6) |
|---|---|---|---|---|---|---|
| $\Delta \ln(1+\tau^*_{igt})$ | -1.064*** | -1.072*** | 0.059 | 1.059*** | | |
| | (0.1920) | (0.1901) | (0.1495) | (0.1495) | | |
| $\Delta \ln x_{igt}$ | | | | | -0.055 | |
| | | | | | (0.1358) | |
| $\Delta \ln p^X_{igt}(1+\tau^*_{igt})$ | | | | | | -1.012*** |
| | | | | | | (0.1786) |
| Product FE | Y | Y | Y | Y | Y | Y |
| Sector × Time FE | Y | Y | Y | Y | Y | Y |
| 1st-stage $F$ | | | | | 24.120 | 58.295 |
| Bootstrap CI | | | | | [-0.270,0.260] | [0.161,1.302] |
| $R^2$ | 0.058 | 0.055 | 0.028 | 0.028 | 0.070 | 0.165 |
| $N$ | 162,054 | 161,494 | 161,494 | 161,494 | 161,494 | 161,494 |

Note: The table reports the variety-level export responses to U.S. import tariffs. Columns (1)–(4) report reduced-form regressions of different export outcomes (export values, quantities, before-duty unit values, and duty-inclusive unit values) on the tariff changes. Column (5) reports the IV estimation of Chinese (inverse) export supply elasticity $\hat{\omega}$ based on equation (2.31), with its first-stage estimation in Column (2). Column (6) reports the IV estimation of foreign import demand elasticity $\hat{\sigma}^*$ based on equation (2.30), with its first-stage estimation in Column (4). Robust standard errors (in parentheses) are clustered at the HS-6 level. 90% bootstrap confidence intervals of ($\hat{\omega}$ and $\hat{\sigma}^*$) were constructed from 1000 samples. The symbols $^*$, $^{**}$, and $^{***}$ indicate statistical significance at the 10%, 5%, and 1% level, respectively. Sample: monthly variety-level export data from 2017:1 to 2019:12.

Table 2.7: Pre-trend Tests for Chinese Imports and Exports

Panel A1: China's retaliatory tariffs on U.S. products

| | $\overline{\Delta \ln p^*_{ig} m_{ig}}$ | $\overline{\Delta \ln m_{ig}}$ | $\overline{\Delta \ln p^*_{ig}}$ | $\overline{\Delta \ln p_{ig}}$ |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| $\Delta \ln(1+\tau_{ig})$ | 0.052 | 0.070 | -0.029 | -0.028 |
| | (0.1870) | (0.2249) | (0.1452) | (0.1452) |
| Sector FE | Y | Y | Y | Y |
| $R^2$ | 0.012 | 0.020 | 0.014 | 0.014 |
| $N$ | 5,064 | 4,951 | 4,951 | 4,950 |

Panel A2: China's MFN tariff cuts

| | $\overline{\Delta \ln p^*_{ig} m_{ig}}$ | $\overline{\Delta \ln m_{ig}}$ | $\overline{\Delta \ln p^*_{ig}}$ | $\overline{\Delta \ln p_{ig}}$ |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| $\Delta \ln(1+\tau_{ig})$ | 0.720 | 0.803 | 0.115 | 0.115 |
| | (0.6089) | (0.6978) | (0.4236) | (0.4237) |
| Country $\times$ Sector FE | Y | Y | Y | Y |
| Product FE | Y | Y | Y | Y |
| $R^2$ | 0.144 | 0.144 | 0.132 | 0.132 |
| $N$ | 66,886 | 64,844 | 64,844 | 64,820 |

Panel B: U.S. tariff increases on Chinese exports

| | $\overline{\Delta \ln p^X_{ig} x_{ig}}$ | $\overline{\Delta \ln x_{ig}}$ | $\overline{\Delta \ln p^X_{ig}}$ | $\overline{\Delta \ln p^X_{ig}(1+\tau^*_{ig})}$ |
|---|---|---|---|---|
| | (5) | (6) | (7) | (8) |
| $\Delta \ln(1+\tau^*_{ig})$ | 0.037 | 0.073 | -0.002 | 0.003 |
| | (0.1204) | (0.1118) | (0.0801) | (0.0771) |
| Sector FE | Y | Y | Y | Y |
| $R^2$ | 0.007 | 0.012 | 0.005 | 0.005 |
| $N$ | 5,483 | 5,473 | 5,473 | 5,445 |

Note: The table reports pre-trend tests for Chinese imports (Panels A1 and A2) and exports (Panel B) at the variety level. The dependent variables are the average monthly change of trade outcome variables during 2017:1–2017:12 in terms of before-duty trade value, quantity, before-duty unit value and duty-inclusive unit value. Panels A1 and B regress the pre-war trade outcomes of Chinese imports from (exports to) the U.S. on the (latest revised) tariff changes during the trade war period 2018:1–2019:12. Panel A2 regresses the trade outcomes of Chinese imports from non-U.S. sources on China's tariff changes on non-U.S. sources of imports during the trade war. Robust standard errors (in parentheses) are clustered at the product level (Panels A1 and B), and product and country level (Panel A2), respectively. The symbols $^*$, $^{**}$, and $^{***}$ indicate statistical significance at the 10%, 5%, and 1% level, respectively. Sample: monthly variety-level import and export data from 2017:1–2017:12 for the pre-trend variables, and 2018:1–2019:12 for the tariff changes.

Table 2.8: Aggregate Impacts

| | $EV^X$<br>(1) | $EV^M$<br>(2) | $\Delta R$<br>(3) | $EV$<br>(4) |
|---|---|---|---|---|
| **2018–2019 trade war** | | | | |
| change ($ b) | -32.968 | -6.906 | 1.976 | -37.898 |
| | [-45.159, 0.786] | [-15.524, 0.874] | [1.360, 3.708] | [-52.282, -3.153] |
| change (% GDP) | -0.272 | -0.057 | 0.016 | -0.312 |
| | [-0.372,0.006] | [-0.128, 0.007] | [0.011,0.031] | [-0.431, -0.026] |
| **2018–2019 trade war (w/o China's MFN tariff cuts)** | | | | |
| change ($ b) | -29.899 | -11.002 | 5.728 | -35.173 |
| | [-41.841, 8.955] | [-19.590, -3.472] | [5.149, 7.977] | [-49.934, 6.157] |
| change (% GDP) | -0.246 | -0.091 | 0.047 | -0.290 |
| | [-0.345, 0.074] | [-0.161, -0.029] | [0.042, 0.066] | [-0.411, 0.051] |
| **2018–2019 trade war (w/o retaliation by China)** | | | | |
| change ($ b) | -37.254 | 0.000 | -1.667 | -38.921 |
| | [-49.834, -12.266] | [-8.296, 7.719] | [-1.756, -0.755] | [-53.614, -13.211] |
| change (% GDP) | -0.307 | 0.000 | -0.014 | -0.321 |
| | [-0.410, -0.101] | [-0.068, 0.064] | [-0.014, -0.006] | [-0.442, -0.109] |

Note: The table reports the aggregate impact in Column (4) and its decomposition into $EV^X$, $EV^M$, and tariff revenue ($\Delta R$) in Columns (1)–(3). The top panel reports the effects from the 2018–2019 trade war. The bottom two panels simulate hypothetical scenarios, where China retaliated against the U.S. but did not implement MFN tariff cuts, and where China neither retaliated against the U.S. nor implemented MFN tariff cuts. The first row in each panel reports the overall impact of each term in billions of US$. The third row scales the value by 2017 GDP of China. These numbers are computed using the model described in Section 2.3 and Appendix 2.6, with $\{\hat{\sigma} = 1.120, \hat{\eta} = 1.087, \hat{\kappa} = 1.173, \hat{\omega}^* = \mathbf{0}, \hat{\sigma}^* = 1.012\}$. Bootstrapped 90% confidence intervals based on 1,000 simulations of the estimated parameters are reported in brackets.

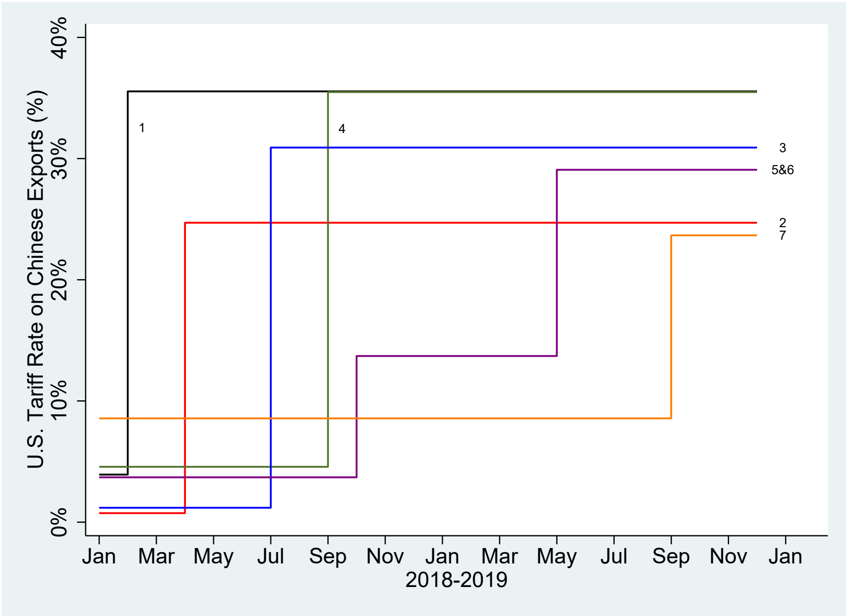
Table 2.9: Simulated Trade Diversion Impacts of the Trade War 2018–2019

| | Δ trade volume (1) | Trade share w/o war (2) | Trade share with war (3) |
|---|---|---|---|
| **Panel A. Imports** | | | |
| U.S. | -13.97% | 9.15% | 8.21% |
| R.O.W. | -3.21% | 90.85% | 91.79% |
| North America | -12.11% | 11.05% | 10.13% |
| Canada | -3.36% | 1.20% | 1.21% |
| Mexico | -2.90% | 0.70% | 0.70% |
| Asia | -3.37% | 52.41% | 52.86% |
| Japan | -2.73% | 9.80% | 9.95% |
| Korea | -3.53% | 10.55% | 10.62% |
| Taiwan | -3.54% | 9.24% | 9.30% |
| ASEAN | -3.52% | 12.61% | 12.70% |
| Europe | -2.45% | 19.13% | 19.48% |
| France | -2.94% | 1.61% | 1.63% |
| Germany | -1.83% | 5.73% | 5.87% |
| The UK | -0.43% | 1.30% | 1.35% |
| **Panel B. Exports** | | | |
| U.S. | -18.64% | 19.20% | 16.19% |
| R.O.W. | 0.03% | 80.80% | 83.81% |
| North America | -15.95% | 22.21% | 19.35% |
| Canada | 0.03% | 1.41% | 1.46% |
| Mexico | 0.03% | 1.60% | 1.66% |
| Asia | 0.02% | 48.70% | 50.50% |
| Japan | 0.03% | 6.08% | 6.30% |
| Korea | 0.03% | 4.58% | 4.75% |
| Taiwan | 0.00% | 1.94 % | 2.01% |
| ASEAN | 0.02% | 13.93% | 14.45% |
| Europe | 0.03% | 18.93% | 19.64% |
| France | 0.03% | 1.23% | 1.28% |
| Germany | 0.03% | 3.16% | 3.28% |
| The UK | 0.03% | 2.54% | 2.63% |

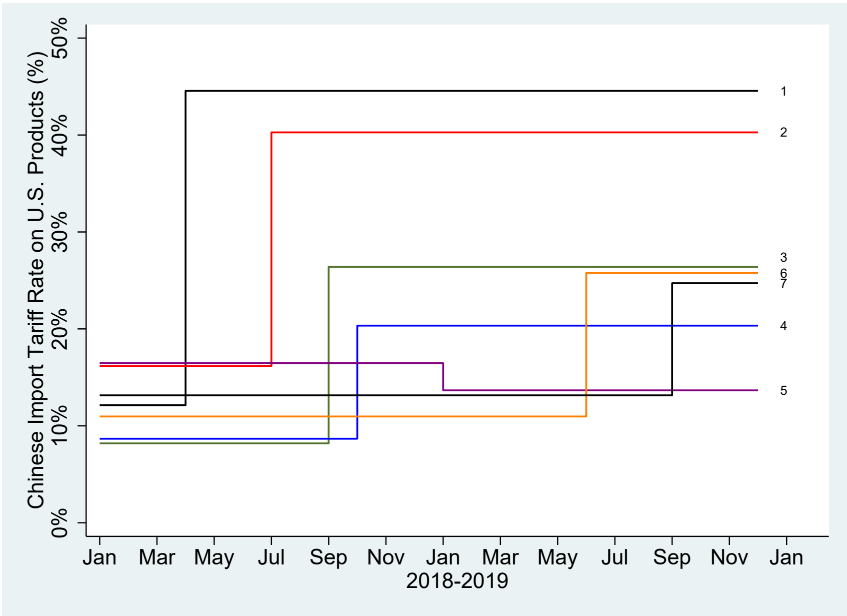
Note: The table reports the simulated changes in China's imports from and exports to its trading partners due to the trade war, using the 2017 Chinese economy given the tariff changes of 2018:1–2019:12. Section 2.6 provides the formulas. Columns (2) and (3) report the trade shares by regions/countries without the trade war and as a result of the trade war.

Figure 2.1: Trade War Timeline

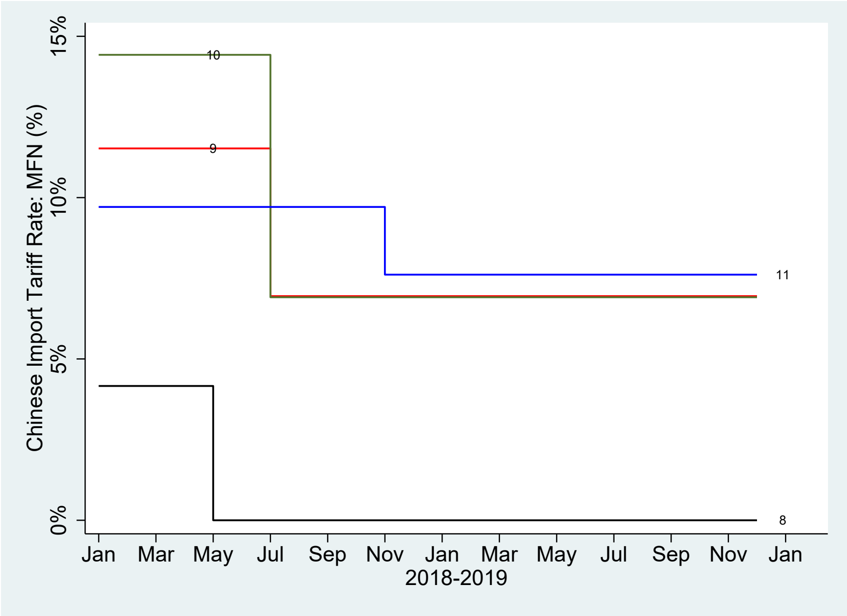
(A) U.S. tariffs on Chinese exports




(B1) Chinese retaliatory tariffs (on imports from U.S.)



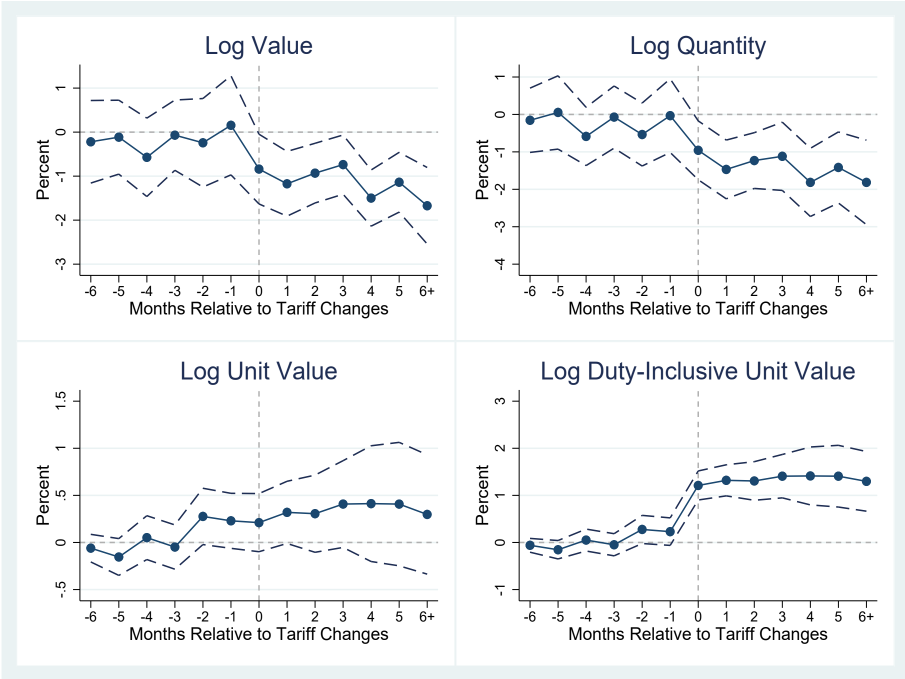
(B2) Chinese MFN tariff cut




Note: The figure shows the unweighted average tariff rate of targeted import and export varieties for each tariff wave before and after they were targeted. The numbering of the events corresponds to those in Table 2.1. Refer to the Data Appendix for additional details on the construction of tariff rates and the scaling of tariff increases when the implementation date is not on the first day of the month. In drawing the above diagram, the implementation month is taken to be the current month if the implementation date is before the 15th of the month and the next month otherwise.

Figure 2.2: Dynamic Specification Tests

(A) Tariffs on Chinese Imports

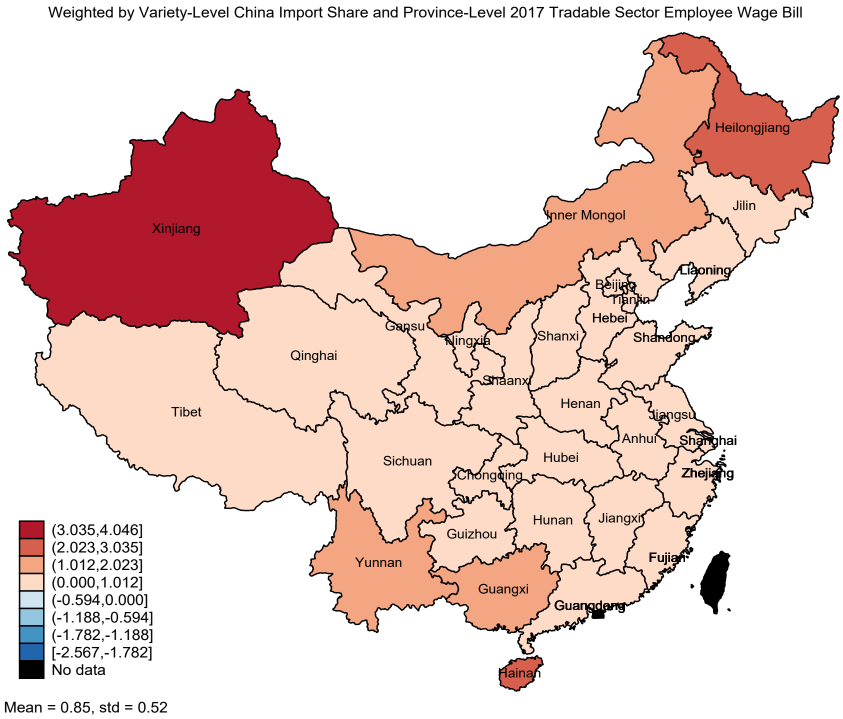



(B) Tariffs on Chinese Exports

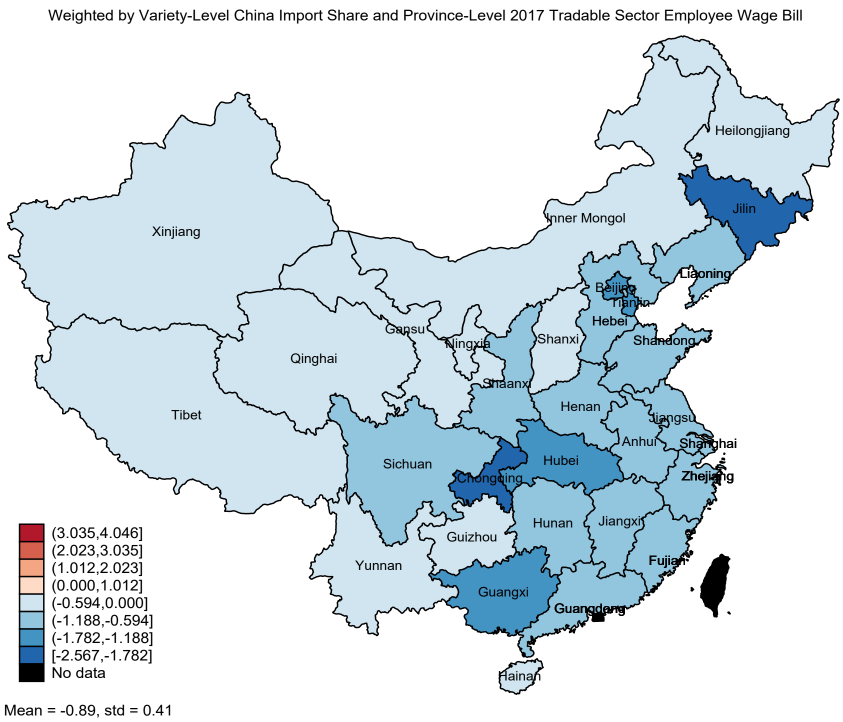

Note: Figures plot cumulative sum of $\beta$ coefficients from the regression (2.33). Standard errors are clustered by country and HS-8 for imports; and by HS-6 for exports (with respect to the U.S. market). Error bands show 95% confidence intervals. Sample: variety-level import and export data for 2017:1–2019:12. As in Fajgelbaum et al. (2020), we replace missing leading and lagged tariff changes with zeros and include indicators for those missing values.

Figure 2.3: Regional Exposure to Tariff Increase of China and U.S.

(A) China's Tariff Increase on U.S. Imports, 2018–2019

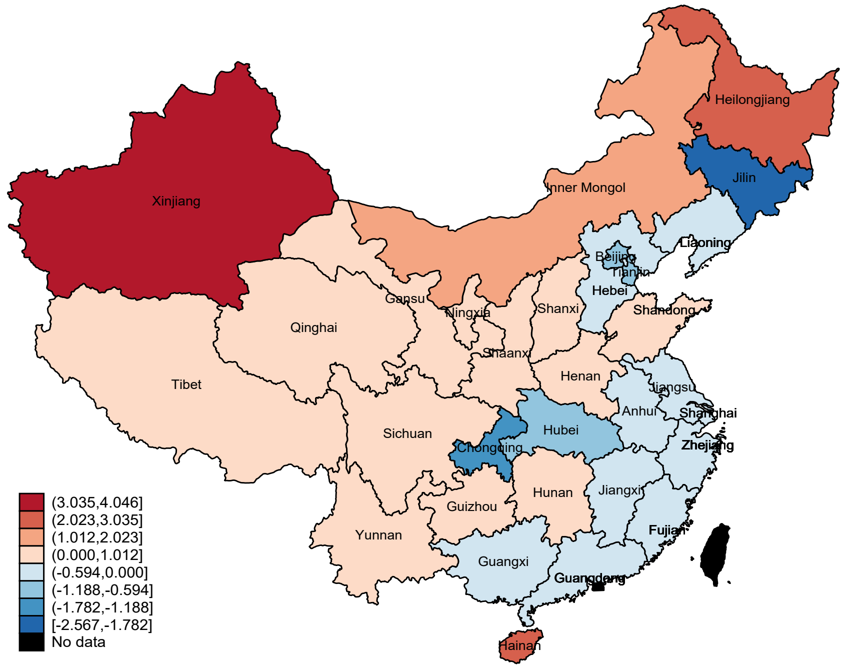



(B) China's MFN Tariff Decrease on Non-U.S. Imports, 2018–2019



## (C) China's Net Tariff Increase on Imports, 2018–2019

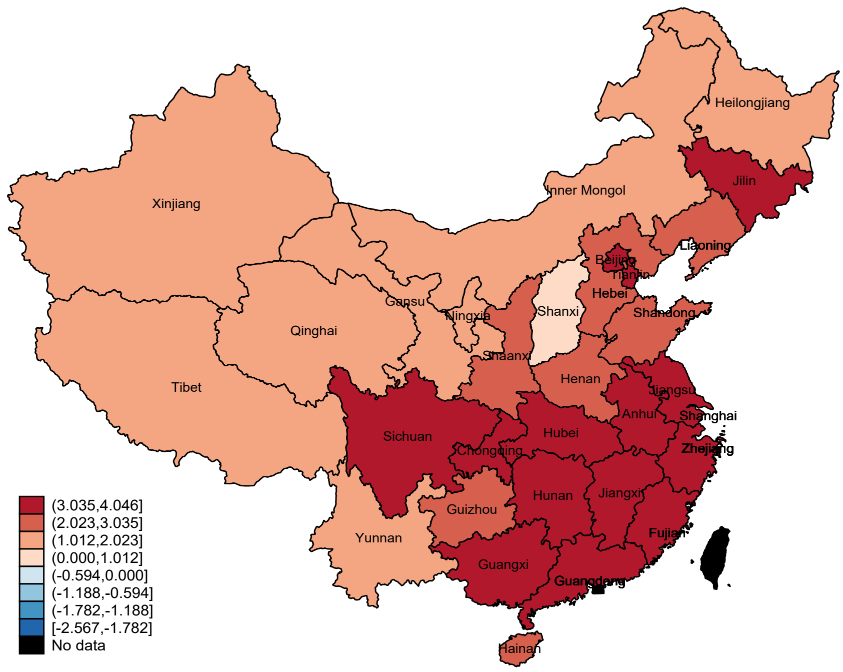
Weighted by Variety-Level China Import Share and Province-Level 2017 Tradable Sector Employee Wage Bill




Mean = 0.01 , std = 0.78

## (D) U.S. Tariff Increase on China's Exports, 2018–2019

Weighted by Variety-Level China Export Share and Province-Level 2017 Tradable Sector Employee Wage Bill

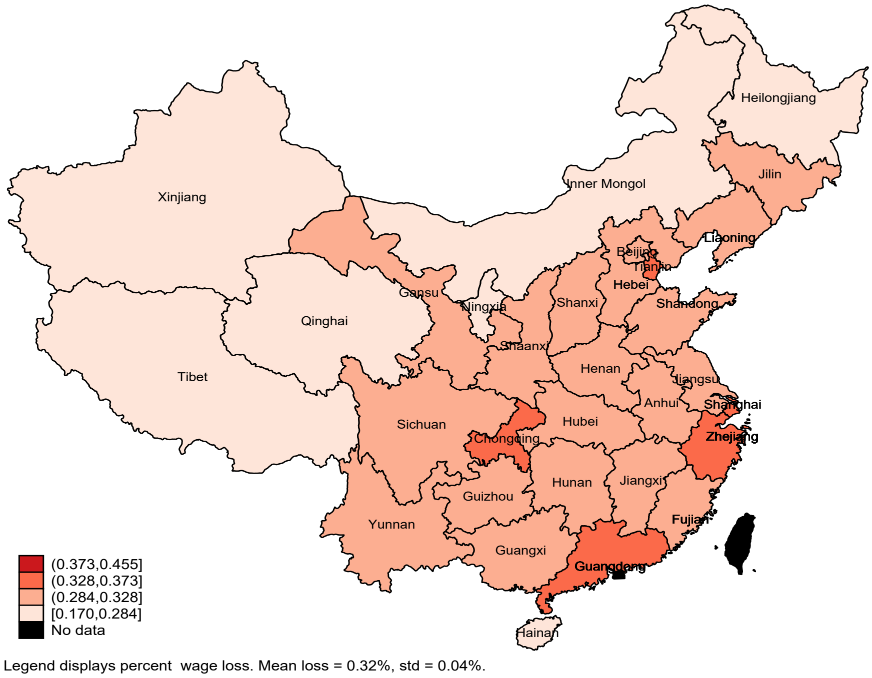



Mean = 3.21 , std = 0.87

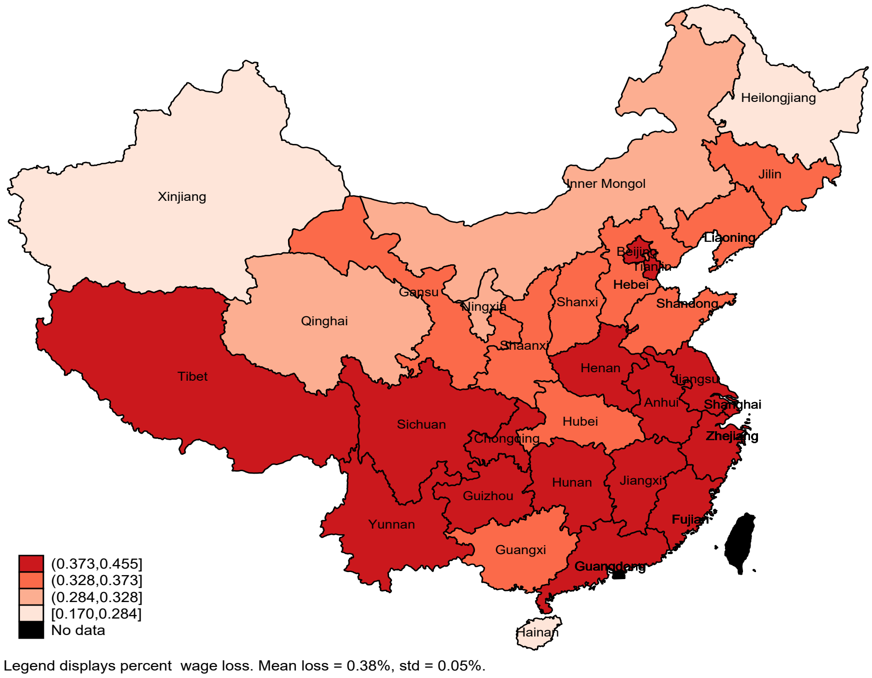
Note: The figure shows province-level exposure to China's tariff increases on U.S. imports (Panel A), China's MFN tariff decreases on non-U.S. imports (Panel B), China's net tariff increase (Panel C), and U.S. tariff increase on China's exports (Panel D), in relation to the trade war during 2018–2019, weighted by 2017 variety-level China trade shares (constructed from customs data) and by 2017 province-level tradable sector employee wage bill (constructed from China Labor Statistical Yearbook). Darker shades indicate exposure to larger tariff changes. Values indicate percentage point tariff changes.

Figure 2.4: Simulated Real Wage Impacts of the Trade War

(A) Tradable Real Wage Loss from Tariff Increases of China and U.S.



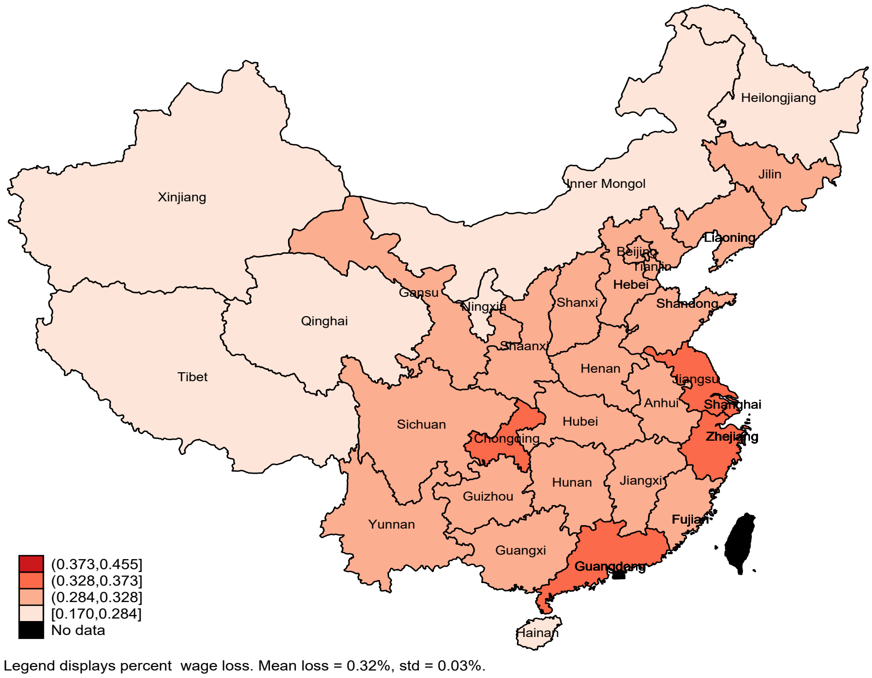

(B) Tradable Real Wage Loss from Tariff Increases of China and U.S. (w/o the MFN tariff adjustment by China)



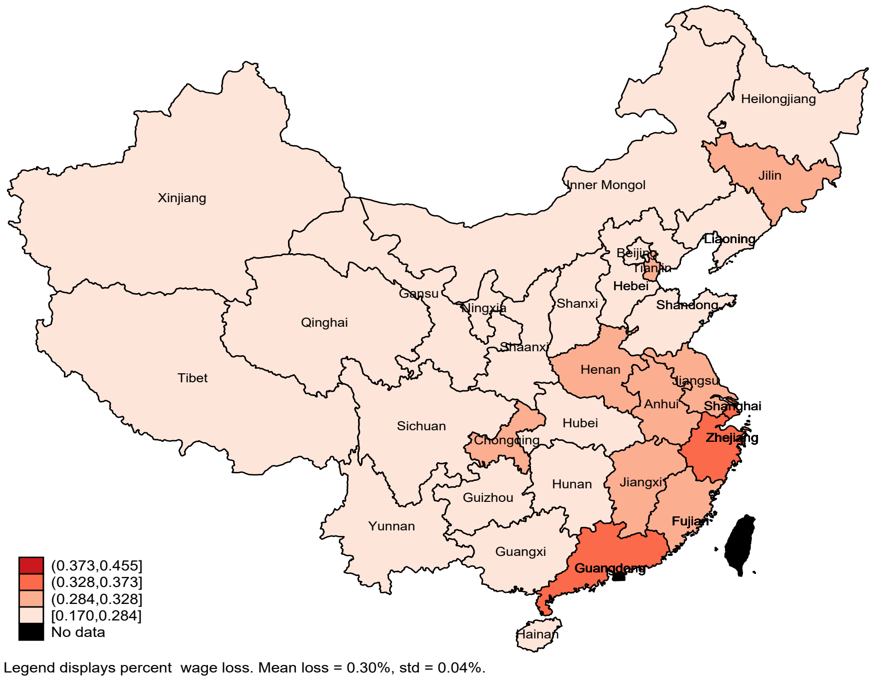

Note: The figure shows province-level mean tradable real wage losses as simulated from the model. Panel A shows losses in the full trade war scenario. Panel B shows losses in the full trade war scenario but without the MFN tariff cuts. Darker shades indicate greater losses. Values indicate percent real wage losses.

Figure 2.5: Simulated Real Expenditure Impacts of the Trade War

(A) Real Expenditure Loss from Tariff Increases of China and U.S.




(B) Real Expenditure Loss from Tariff Increases of China and U.S.
(w/o the MFN tariff adjustment by China)




Note: The figure shows province-level mean real expenditure losses as simulated from the model. Panel A shows losses in the full trade war scenario. Panel B shows losses in the full trade war scenario but without the MFN tariff cuts. Darker shades indicate greater losses. Values indicate percent real expenditure losses.

Table A.1: Effects of Tariff Wars on China's Imports and Exports (Partial Effects)

| | China's tariff increase against U.S. products | | MFN tariff cuts | | Combined | |
|---|---|---|---|---|---|---|
| IMPORT | Δ tariff | Δ import values | Δ tariff | Δ import values | Δ tariff | Δ import values |
| Varieties | 11.72% | −13.14% | −3.10% | 3.48% | 3.25% | −3.64% |

| | U.S. tariff increase against Chinese products | |
|---|---|---|
| EXPORT | Δ tariff | Δ export values |
| Varieties | 24.18% | −24.48% |

Note: The table reports the weighted average change in the tariff rates of targeted varieties, and the implied change in the trade values of the targeted varieties. The formulas used are: i) $\overline{\Delta \ln \left(p^*_{ig} m_{ig}\right)}^{wa} \equiv \sum_{ig} -\hat{\sigma} \frac{1+\hat{\omega}^*}{1+\hat{\omega}^* \hat{\sigma}} \Delta \ln (1+\tau_{ig}) \cdot \left(p^*_{ig} m_{ig}\right) / \sum_{ig} \left(p^*_{ig} m_{ig}\right) \equiv -\hat{\sigma} \frac{1+\hat{\omega}^*}{1+\hat{\omega}^* \hat{\sigma}} \overline{\Delta \ln (1+\tau_{ig})}^{wa}$ for imports, where the response ratio $-\hat{\sigma} \frac{1+\hat{\omega}^*}{1+\hat{\omega}^* \hat{\sigma}}$ is implied by the demand and supply equations (2.22) and (2.23); and ii) $\overline{\Delta \ln \left(p^X_{ig} x_{ig}\right)}^{wa} \equiv \sum_{ig} -\hat{\sigma}^* \frac{1+\hat{\omega}}{1+\hat{\omega}\hat{\sigma}^*} \Delta \ln \left(1+\tau^*_{ig}\right) \cdot \left(p^X_{ig} x_{ig}\right) / \sum_{ig} \left(p^X_{ig} x_{ig}\right) \equiv -\hat{\sigma}^* \frac{1+\hat{\omega}}{1+\hat{\omega}\hat{\sigma}^*} \overline{\Delta \ln \left(1+\tau^*_{ig}\right)}^{wa}$ for exports, where the response ratio $-\hat{\sigma}^* \frac{1+\hat{\omega}}{1+\hat{\omega}\hat{\sigma}^*}$ is implied by the demand and supply equations (2.30) and (2.31). The calculations use the elasticity estimates reported in Tables 2.3 and 2.6, the pre-war duty-exclusive trade value of 2017 (as weights), and the latest revised tariff change for each variety observed during the period 2018:1–2019:12 (as the shock).

# Chapter 3

# Extension to Chang et al. (2021) with a China-U.S.-ROW Model

## 3.1 Introduction

In Chapter 2, the model we used to analyze the impacts of the 2018-19 China-U.S. trade war on the Chinese economy assumed a detailed general equilibrium structure for the local economy (China), but had minimal setup for the foreign countries. In other words, all the trading partners of China were grouped into one economy, which did not have any general equilibrium interactions with China in response to the tariff war. Instead, it acted only as an auxiliary that complemented the economic structure of the Chinese economy and its response was totally governed by a pair of import demand and export supply elasticities[1]. This kind of simplification could potentially lead to underestimation about the impacts of the trade war between the two economies. Since the United States is the most important trading partner of China and the detailed data about the U.S. economy is readily available, we extended the 2-economy model introduced in the second chapter (China and the rest of the world - ROW) to a 3-economy framework, China-U.S.-ROW, in order to simultaneously incorporate the general equilibrium (GE) adjustments in the two largest economies in response to the trade war.

In the China-U.S.-ROW framework, the interaction between China and U.S. lies

[1] In Fajgelbaum et al. (2020), similarly, they conducted the analyses under U.S.-ROW framework.

in the market clearing conditions for all tradeable products, with the modeling of the domestic economic structure in the two countries remaining unchanged. In China, the production of a tradeable variety is affected by the import demand from the U.S., which is determined not only directly by the tariff policies but also indirectly through the consumption and production reallocation effects. The same applies vice versa for the U.S. Compared to the system constructed in Chapter 2 that only contains parameters and endogenous variables in the local economy, now we need to take into account the general equilibrium adjustments in both two economies and solve the system simultaneously.

We first collect and compile the trade and tariff data on the U.S. side from January 2018 to December 2019 and re-estimate the import demand and export supply elasticities from the U.S. perspective in a symmetric way, similar to what we did on the China side. During this stage, the original HS10 products in the U.S. are reconciled according to the HS8 classification system in China. This ensures that the two economies have the same product-level dimension, which is the linkage between China and the U.S. in this 3-economy framework. Then we solve the system based on first-order approximations around the pre-war equilibrium, as described in Chapter 2.

We observe significant increases in the impacts of the trade war on both economies when we consider the general equilibrium adjustments in the U.S. economy, as expected. The aggregate loss to the Chinese economy grows by nearly 50% from \$36.9 billion in the China-ROW setup to \$54.5 billion in the China-U.S.-ROW model. On the other hand, the increase on the U.S. side is relatively modest, at 12% from \$24.8 billion to \$27.7 billion.

While the aggregate loss to the U.S. is only half of that to China, the loss experienced by American buyers of imports is substantially larger than that of Chinese importers (\$44 billion versus \$7 billion). We observe the same pattern regarding the role of the most favored nation (MFN) tariff cut policy implemented by the Chinese government in the 3-economy model as in the China-ROW setup. China's MFN tariff reductions on non-U.S. products help cushion the negative impacts on its importers significantly, but this comes at the cost of its producers, resulting in an overall larger aggregate loss.

## 3.2 Model

We start from the market clearing condition for tradeable good $g$ under the China-U.S.-ROW framework:

$$q_g = d_g + \sum_{i \in \mathscr{ROW}_g} \delta_{ig} x_{ig} + \delta_{US,g} x_{US,g}$$

Similar to the derivation of equation (A.5), we can get the following expression in the new setup:

$$\begin{aligned}\hat{Q}_s &= \sum_{g \in \mathscr{G}_s} \frac{p_{Dg} d_g}{p_s Q_s} \hat{d}_g + \sum_{g \in \mathscr{G}_s} \sum_{i \in \mathscr{ROW}_g} \frac{p^X_{ig} x_{ig}}{p_s Q_s} \hat{x}_{ig} + \sum_{g \in \mathscr{G}_s} \frac{p^X_{US,g} x_{US,g}}{p_s Q_s} \hat{x}_{US,g} \\ &= \frac{P_{Ds} D_s}{p_s Q_s} \left( \hat{E}_s + (\kappa - 1) \hat{P}_s - \kappa \hat{p}_s \right) - \sigma^* \hat{p}_s \sum_{g \in \mathscr{G}_s} \sum_{i \in \mathscr{ROW}_g} \frac{p^X_{ig} x_{ig}}{p_s Q_s} + \sum_{g \in \mathscr{G}_s} \frac{p^{*US}_{CN,g} m^{US}_{CN,g}}{p_s Q_s} \hat{m}^{US}_{CN,g},\end{aligned} \tag{3.1}$$

where we use the fact that $\hat{x}_{ig} = -\sigma^* \left( \frac{d\tau^*_{ig}}{1+\tau^*_{ig}} + \hat{p}_s \right) = -\sigma^* \hat{p}_s$ for any $i \in \mathscr{ROW}_g$ since the ROW does not impose any tariff changes on Chinese products, i.e., $d\tau^*_{ig} = 0$. The superscript "US" means that Combining this equation with equation (A.6) yields:

$$\hat{p}_s = \frac{\frac{P_{Ds} D_s}{p_s Q_s} \left( \hat{E}_s + (\kappa - 1) \hat{P}_s \right) + \frac{\alpha_{Is}}{\alpha_{Ks}} \hat{\phi}_s + \sum_{r \in \mathscr{R}} \frac{p_s Q_{sr}}{p_s Q_s} \frac{\alpha_{Ls}}{\alpha_{Ks}} \hat{w}_{sr} + \sum_{g \in \mathscr{G}_s} \frac{p^{*US}_{CN,g} m^{US}_{CN,g}}{p_s Q_s} \hat{m}^{US}_{CN,g}}{\frac{1-\alpha_{Ks}}{\alpha_{Ks}} + \frac{P_{Ds} D_s}{p_s Q_s} \kappa + \sigma^* \sum_{g \in \mathscr{G}_s} \sum_{i \in \mathscr{ROW}_g} \frac{p^X_{ig} x_{ig}}{p_s Q_s}}, \tag{3.2}$$

where $\hat{m}^{US}_{CN,g}$ has the same expression as in the China-ROW general equilibrium:

$$\begin{aligned}\hat{m}^{US}_{CN,g} =& \frac{1}{1 + \omega^{*US} \sigma^{US}} \left[ \hat{E}^{US}_s + (\kappa^{US} - 1) \hat{P}^{US}_s + (\eta^{US} - \kappa^{US}) \hat{P}^{US}_{Ms} + (\sigma^{US} - \eta^{US}) \hat{p}^{US}_{Mg} \right] \\ & - \frac{\sigma^{US}}{1 + \omega^{*US} \sigma^{US}} \frac{d\tau^{US}_{CN,g}}{1 + \tau^{US}_{CN,g}}\end{aligned}$$

For the United States, everything is the same in deriving $\hat{p}^{US}_s$ except that $d\tau^{*US}_{ig} \neq 0$ for some $i \in \mathscr{ROW}_g$ because some countries retaliated against the U.S. Hence

$$\begin{aligned}\hat{Q}^{US}_s =& \frac{P^{US}_{Ds} D^{US}_s}{p^{US}_s Q^{US}_s} \left( \hat{E}^{US}_s + (\kappa^{US} - 1) \hat{P}^{US}_s - \kappa^{US} \hat{p}^{US}_s \right) \\ & - \sigma^{*US} \sum_{g \in \mathscr{G}^{US}_s} \sum_{i \in \mathscr{ROW}_g} \frac{p^{X,US}_{ig} x^{US}_{ig}}{p^{US}_s Q^{US}_s} \left( \frac{d\tau^{*US}_{ig}}{1 + \tau^{*US}_{ig}} + \hat{p}^{US}_s \right) + \sum_{g \in \mathscr{G}^{US}_s} \frac{p^*_{US,g} m_{US,g}}{p^{US}_s Q^{US}_s} \hat{m}_{US,g}\end{aligned} \tag{3.3}$$

and it follows that

$$\hat{p}_s^{US} = \frac{\begin{array}{c}\frac{P_{Ds}^{US} D_s^{US}}{p_s^{US} Q_s^{US}} \left(\hat{E}_s^{US} + (\kappa^{US} - 1)\hat{P}_s^{US}\right) + \frac{\alpha_{Is}^{US}}{\alpha_{Ks}^{US}} \hat{\phi}_s^{US} + \sum_{r \in \mathscr{R}^{US}} \frac{p_s^{US} Q_{sr}^{US}}{p_s^{US} Q_s^{US}} \frac{\alpha_{Ls}^{US}}{\alpha_{Ks}^{US}} \hat{w}_{sr}^{US} \\ - \sigma^{*US} \sum_{g \in \mathscr{G}_s^{US}} \sum_{i \in \mathscr{ROW}_g} \frac{p_{ig}^{X,US} x_{ig}^{US}}{p_s^{US} Q_s^{US}} \frac{d\tau_{ig}^{*US}}{1+\tau_{ig}^{*US}} + \sum_{g \in \mathscr{G}_s^{US}} \frac{p_{US,g}^{*} m_{US,g}}{p_s^{US} Q_s^{US}} \hat{m}_{US,g}\end{array}}{\frac{1-\alpha_{Ks}^{US}}{\alpha_{Ks}^{US}} + \frac{P_{Ds}^{US} D_s^{US}}{p_s^{US} Q_s^{US}} \kappa^{US} + \sigma^{*US} \sum_{g \in \mathscr{G}_s^{US}} \sum_{i \in \mathscr{ROW}_g} \frac{p_{ig}^{X,US} x_{ig}^{US}}{p_s^{US} Q_s^{US}}}, \tag{3.4}$$

where $\hat{m}_{US,g}$ is of a symmetric form with $\hat{m}_{CN,g}^{US}$:

$$\hat{m}_{US,g} = \frac{1}{1+\omega^* \sigma} \left[\hat{E}_s + (\kappa - 1)\hat{P}_s + (\eta - \kappa)\hat{P}_{Ms} + (\sigma - \eta)\hat{p}_{Mg}\right] - \frac{\sigma}{1+\omega^* \sigma} \frac{d\tau_{US,g}}{1+\tau_{US,g}}$$

Now we can observe from equations (3.2) and (3.4) how the (indirect) GE adjustments in the other economy impact the production activities in the local economy. This interaction between the two major economies is absent in the 2-economy setup discussed in the previous chapter.

The expressions for other endogenous variables and the numerical implementation remain the same as those presented in Chapter 2.

## 3.3 Welfare Analysis

Table 3.2 reports the aggregate impact of the trade war and its decomposition into $EV^X$, $EV^M$, and tariff revenue ($\Delta R$) on China and the United States. The top panel shows the effects under the China-U.S.-ROW framework, which takes into account the interaction of the two largest economies. The bottom panel presents the results under the 2-Economy setups, China-ROW and U.S.-ROW, sourced from Chang et al. (2021) and Fajgelbaum et al. (2021), respectively. In addition to the effects of the 2018-19 trade war, we also examine two alternative hypothetical scenarios: one where China retaliated against the U.S. but did not implement MFN tariff cuts, and another where China neither retaliated nor implemented MFN tariff cuts. Each panel reports the annual monetary equivalent at 2017 prices in billions of US dollars and the figures relative to 2017 GDP of China/U.S. The model parameters used in this welfare analysis are listed in Table 3.1.

Compared to the impact on the Chinese economy analyzed in the previous chapter under the China-ROW framework, the aggregate loss is much larger at $54.5 billion when we incorporate the interactions between the U.S. and China. This is mainly due to the term $EV^X$, indicating a more severe drop in export price indices and consequently a greater loss for Chinese exporters when considering the GE adjustments in the two economies. For the U.S. economy, the deterioration in the aggregate loss from the 2-economy to the 3-economy model is relatively mild, going from \$24.8 billion to \$27.7 billion. While the situation improves significantly for American buyers of imports (the loss decreases from \$114 billion to \$44 billion), the gains for producers and the tariff revenue surplus resulting from the U.S. tariff hike decrease substantially.

The pattern regarding the role of the MFN tariff cut policy implemented by the Chinese government remains the same in the China-U.S.-ROW model. The adjustment in MFN tariff rates on non-U.S. sources of imports helped reduce the loss for Chinese buyers of imports and shifted part of the burden back to the producers. Overall, the aggregate loss in $EV$ is slightly larger.

In conclusion, the general equilibrium adjustments in China and the U.S. are crucial for evaluating the impacts of the trade war. Failing to account for the interaction between the two central economies in the model would lead to a significant underestimation of the trade war's effects. The trade war did not benefit either producers or consumers in the United States, but it did significantly harm Chinese exporters at the expense of its own consumers.

## 3.4 Conclusion

In this chapter, we expand upon the 2-economy models used in Chang et al. (2021) and Fajgelbaum et al. (2020), which focus solely on the local economy, by introducing a China-U.S.-ROW framework. This framework allows us to capture the general equilibrium interactions between the two largest economies in the world and evaluate the impact of the 2018-19 trade war. As expected, neglecting the general equilibrium adjustments in China and the U.S. could significantly underestimate the costs of the tariff war on both economies. Under the China-U.S.-ROW framework, the aggregate welfare loss was found to be 50% larger for the Chinese economy and 12% higher for the U.S. economy.

The estimated aggregate loss to the Chinese economy amounted to \$54.5 billion (0.44% of 2017 GDP), which is twice the loss experienced by the U.S. economy

($17.4 billion). In contrast to the result indicating that U.S. consumers of imported goods bore the majority of the losses, the adverse impacts on the Chinese side were primarily shouldered by its exporters. The MFN tariff cuts implemented by the Chinese government helped alleviate the negative impacts on Chinese importers to a significant extent. However, this came at the expense of its producers, resulting in an overall larger aggregate loss.

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**_ , _ , _ , and _** , "Updates to Fajgelbaum et al. (2020) with 2019 tariff waves," *Work. Pap., Princeton Univ., Princeton, NJ*, 2021.

Table 3.1: Estimates of Elasticities: 3-Economy v.s 2-Economy

| **3-Economy** | | | | | | | |
|---|---|---|---|---|---|---|---|
| $\sigma$ | $\eta$ | $\kappa$ | $\sigma^*$ | $\sigma^{US}$ | $\eta^{US}$ | $\kappa^{US}$ | $\sigma^{*US}$ |
| 1.12 | 1.087 | 1.173 | 1.075 | 2.236 | 4.926 | 1.05 | 1.075 |
| **2-Economy: China** | | | | **2-Economy: U.S.** | | | |
| $\sigma$ | $\eta$ | $\kappa$ | $\sigma^*$ | $\sigma^{US}$ | $\eta^{US}$ | $\kappa^{US}$ | $\sigma^{*US}$ |
| 1.12 | 1.087 | 1.173 | 1.012 | 2.53 | 1.53 | 1.19 | 1.04 |

*Notes:* The table shows the estimates of different elasticities. The above panel presents the estimation results for the two economies under the China-U.S.-ROW framework, while the bottom panel reports the results for China and U.S. when we use China-ROW and U.S.-ROW models, respectively. The estimation of $\sigma^{*US}$ exploits the trade and tariff variations from non-China sources. We let $\sigma* = \sigma^{*US}$ because $\sigma^{*US}$ is more reliable in the sense that there is no tariff variation across non-U.S. countries from China's perspective (only the U.S. imposed tariff increases against China) while many countries retaliated against U.S. products.

Table 3.2: Aggregate Impacts: 2-Economy v.s 1-Economy

| | **3-Economy** | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | China | | | | U.S. | | | |
| | $EV^X$ (1) | $EV^M$ (2) | $\Delta R$ (3) | $EV$ (4) | $EV^X$ (5) | $EV^M$ (6) | $\Delta R$ (7) | $EV$ (8) |
| **Full war** | | | | | | | | |
| $ billion | -48.53 | -7.09 | 1.12 | -54.50 | -1.66 | -44.17 | 18.14 | -27.68 |
| | [-194.738,-5.160] | [-28.113,12.163] | [-4.405,2.949] | [-210.342,-11.802] | [-30.086,18.492] | [-67.078,-41.862] | [-5.705,48.655] | [-95.317,25.047] |
| % GDP | -0.39 | -0.06 | 0.01 | -0.44 | -0.01 | -0.23 | 0.09 | -0.14 |
| | [-1.582 ,-0.042] | [-0.228 ,0.099] | [-0.036 ,0.024] | [-1.709 ,-0.096] | [-0.154 ,0.095] | [-0.343 ,-0.214] | [-0.029 ,0.249] | [-0.488 ,0.128] |
| **Retaliate against U.S. only, no MFN tariff cuts** | | | | | | | | |
| $ billion | -44.99 | -11.24 | 4.86 | -51.37 | -1.34 | -44.17 | 18.16 | -27.35 |
| | [-191.210,-1.458] | [-32.208,8.081] | [-1.064,6.905] | [-206.460,-8.568] | [-29.743,19.171] | [-66.923,-41.942] | [-5.682,48.689] | [-94.456,26.931] |
| % GDP | -0.37 | -0.09 | 0.04 | -0.42 | -0.01 | -0.23 | 0.09 | -0.14 |
| | [-1.553 ,-0.012] | [-0.262 ,0.066] | [-0.009 ,0.056] | [-1.677 ,-0.070] | [-0.152 ,0.098] | [-0.342 ,-0.215] | [-0.029 ,0.249] | [-0.483 ,0.138] |
| **No action** | | | | | | | | |
| $ billion | -51.16 | 0.00 | -2.43 | -53.59 | 6.53 | -44.17 | 18.73 | -18.91 |
| | [-192.260,-8.228] | [-18.382,18.063] | [-6.945,-1.112] | [-196.871,-9.785] | [-18.976,25.004] | [-62.510,-42.156] | [-4.931,49.376] | [-80.364,31.470] |
| % GDP | -0.42 | 0.00 | -0.02 | -0.44 | 0.03 | -0.23 | 0.10 | -0.10 |
| | [-1.562 ,-0.067] | [-0.149 ,0.147] | [-0.056 ,-0.009] | [-1.599 ,-0.079] | [-0.097 ,0.128] | [-0.320 ,-0.216] | [-0.025 ,0.253] | [-0.411 ,0.161] |

| | **China: 2-Economy** | | | |
|---|---|---|---|---|
| **Full war** | | | | |
| $ billion | -31.90 | -7.87 | 2.84 | -36.93 |
| | [-43.898, 2.242] | [-16.409, -0.110] | [2.241, 4.619] | [-41.047. -5.094] |
| % GDP | -0.26 | -0.06 | 0.02 | -0.30 |
| | [-0.362,0.018] | [-0.135, -0.001] | [0.018.0.038] | [-0.338, -0.042] |
| **Retaliate against U.S. only, no MFN tariff cuts** | | | | |
| $ billion | -29.18 | -11.53 | 6.17 | -34.54 |
| | [-41.047, 9.933] | [-20.054, -4.032] | [5.589, 8.435] | [-49.029, 6.759] |
| % GDP | -0.24 | -0.10 | 0.05 | -0.28 |
| | [-0.338, 0.082] | [-0.165, -0.033] | [0.046, 0.069] | [-0.404, 0.056] |
| **No action** | | | | |
| $ billion | -36.87 | 0.00 | -1.59 | -38.45 |
| | [-49.299, -12.088] | [-8.294, 7.639] | [-1.670, -0.716] | [-52.986, -13.032] |
| % GDP | -0.30 | 0.00 | -0.01 | -0.32 |
| | [-0.406, -0.100] | [-0.068, 0.063] | [-0.014, -0.006] | [-0.436, -0.107] |

| **U.S: 2-Economy** | | | |
|---|---|---|---|
| **Full war** | | | |
| 24.3 | -114.2 | 65 | -24.8 |
| [15.4,35.2] | [-121.8,-106.5] | [59.0,70.2] | [-39.4,-8.8] |
| 0.13 | -0.61 | 0.35 | -0.13 |
| [0.08,0.19] | [-0.65,-0.57] | [0.32,0.38] | [-0.21,-0.05] |
| **No retaliation at all** | | | |
| 31.8 | -114.1 | 65.9 | -16.4 |
| [24.8,40.1] | [-119.8,-108.4] | [59.9,71.1] | [-28.5,-3.0] |
| 0.17 | -0.61 | 0.35 | -0.09 |
| [0.13,0.22] | [-0.64,-0.58] | [0.32,0.38] | [-0.15,-0.02] |

*Notes:* The table reports the aggregate impact of the trade war and its decomposition into $EV^X$, $EV^M$, and tariff revenue ($\Delta R$) on China and the U.S. The top panel reports the effects under the China-U.S.-ROW framework, while the bottom panel presents the results under China-ROW and U.S.-ROW setups respectively. In the 3-economy framework, except for the impact of the real trade war, we also simulate two hypothetical scenarios, where China retaliated against the U.S. but did not implement MFN tariff cuts, and where China neither retaliated against the U.S. nor implemented MFN tariff cuts. The results for China and U.S. in the 2-economy models are taken from Chang et al. (2021) and Fajgelbaum et al. (2021), respectively. For each scenario, the first row reports the impact of each term in billions of US$. The third row scales the value by 2017 GDP of China/U.S. These numbers are computed using the estimated parameters in corresponding models as reported in Table 3.1. Bootstrapped 90% confidence intervals based on 1,000 simulations of the estimated parameters are reported in brackets.