Climate Hazards and Resilience in the Global Car Industry*

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Abstract

Climate change will increase the frequency and severity of natural disasters. I study the impact of an increase in the likelihood of weather-related disruptions on the spatial organization of firms. Using data on the global car industry and an event-study design, I document that the occurrence of a flood close to an assembly plant significantly reduces car production, which is partially reallocated to other unaffected plants of the same firm. I develop a novel quantitative multiregion model in which firms choose the location and capacity of their production plants to maximize expected profits under uncertainty about potential weather disruptions. In the model, firms have incentives to invest in production capacity in multiple locations to hedge against potential production disruptions in one of their plants. I estimate the model for the global automotive industry and use it to compute plant locations and capacity choices under different probabilities of weather disruptions according to possible climate change scenarios. In response to the heightened risk, I show that firms build additional plants, but these sites are smaller and operate with a larger spare capacity. The spatial reorganization of the firms' plants is costly as it entails sizable productivity losses, resulting in higher consumer prices.

JEL Classifications: F12, F18, F23, L23, Q54, Q56

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1 Introduction

This paper studies how the likelihood of extreme weather events shapes the spatial organization of firms. Climate change will increase the frequency and severity of weather-related natural disasters worldwide. The Sixth Assessment Report of the Intergovernmental Panel of Climate Change (IPCC 2021a) asserts that global warming will cause a proliferation of multiple climate hazards. Given the expected increase in the frequency and intensity of these adverse climate shocks, it is crucial to understand how firms can adapt, how large the resulting adaptation costs could be, and how firm-level adaptations could buffer the impact of climate change on firms' profits and consumer welfare.

As responses to the rise in the frequency of weather disasters caused by a changing climate, this paper explores two potential mechanisms of endogenous adaptation that firms can use to lessen the impact of extreme weather events. First, firms can modify the location, number, and capacity of their production sites. Second, conditional on their plant configuration, firms with multiple production sites can exploit the flexibility built into their plant structure to reallocate production from affected to unaffected plants.

These adaptation mechanisms could entail high costs for firms and societies. When firms reallocate their production facilities across locations in response to climate hazards, they move production away from a more productive place ex-ante to a less productive one. Consumers bear this productivity loss in the form of higher prices and reduced variety, ultimately decreasing welfare. Creating a flexible and resilient production structure is also costly. Setting up multiple plants to hedge against adverse shocks requires a sizable investment in capital structures, and exploiting the flexibility of a multiplant scheme requires building production sites that operate with spare capacity.

I examine these specific adaptation margins in the global car industry.[1] This industry provides an ideal setting for studying this question as it comprises multinational, multiplant firms producing in big physical sites, that are susceptible to weather disasters.[2] To this end, I leverage a rich global dataset that links the production location at the plant level with sales of individual car models. The car industry is large; it commands around 5% of global trade and 6% of employment in advanced economies. It is a major sector in the public discussion and a frequent target of industrial policy.

Numerous anecdotes about the car industry demonstrate these adaptation mechanisms. One striking example corresponds to the case of a Honda plant in Mexico. In June 2018, torrential precipitation affected the city of Celaya in Guanajuato, Mexico. The local Laja River burst its banks and flooded a neighboring industrial park. Among the flooded facilities was a 400-hectare Honda assembly plant that had to suspend operations for nearly three months before full operations

[1] As an anecdote that showcases these mechanisms, in their 2021 Carbon Disclosure Project Report (CDP-BMW 2021) BMW states that flexible production structures allow them to respond to business interruptions caused by physical climate drivers. For example, if the X3 production in Spartanburg (USA) is shut down, they can shift volumes to Rosslyn (South Africa) or Shenyang (China).

[2] In Appendix A, I present a collection of news headlines about extreme weather events that have caused significant disruptions to car production.

could resume. As a result of Honda's careful planning, they had developed another plant in El Salto, Guadalajara, about 160 kilometers away from Celaya, that partially picked up some of the lost production in the affected plant. However, the plant in El Salto had a smaller production capacity than that in Celaya, and therefore production in the alternate site could not fully compensate the loss.[3]

In the first part of the paper, I provide systematic empirical evidence of the disruptive negative consequences of severe floods on car production. Floods are a direct consequence of several meteorological and hydrological phenomena, such as extreme rainfall events, rapid snowmelt, intense tropical cyclones, and coastal storms that raise the sea level temporarily, all of which are likely exacerbated in intensity and severity by climate change.[4] I focus on large-scale flooding events because these disasters typically cause a large amount of economic damage. Floods affect production activities through several channels, namely, direct effects on production operations through damaged facilities and increased difficulty of transporting final goods, material inputs, and labor, as well as other, indirect effects caused by affected infrastructure and disruptions to local supply chains. Moreover, there are data sources available with detailed information about historical floods. The timing of these events is arguably exogenous to local industry characteristics.

Using an event-study design, I find that the occurrence of a severe flood close to a car assembly site causes a long-run decline in the plant's production of around 34%. Additionally, multiplant firms reallocate some of their production to their unaffected locations. By leveraging information on the production of narrowly defined car models, I estimate that when a flood affects a given plant, production in alternative plants that produce at least one of the same models rises by 26.4%.

I develop a multiregion model of optimal plant location to understand how firms adapt to the increasing likelihood of floods and assess the costs of these adaptation mechanisms. In the model, firms are potentially multinational and can operate multiple plants as platforms to serve different markets, as in Helpman et al. (2004) and Tintelnot (2017). Firms choose their production plants' locations and capacities to maximize expected profits. They face uncertainty about the exact productivity of each plant at the time of making an irreversible investment in plant capacity. After capacity is installed, productivity shocks, in the form of adverse weather events, are realized, and firms choose the optimal production flows from each plant to each market, conditional on their sunk plant locations and capacity choices.

In deciding their plant configuration, firms face a tradeoff between proximity, cost minimization, and resilience. Trade costs provide incentives to set up assembly plants close to large markets. Locating plants close to customers might sacrifice setting up plants in locations that minimize production costs. In the model, these two potentially conflicting incentives interact with a third margin, namely, resilience in production. Since negative productivity shocks, in the form of floods, occur with a certain probability, firms have additional incentives to invest in production capacity in multiple locations to hedge against production disruptions in one of their plants.

[3] In Figure A.1 in the Appendix, I show graphical evidence of the flood, its impact on Honda's production in the region and the geographical location of both plants.

[4] See, e.g., IPCC (2021a), Hirabayashi et al. (2021), Bates et al. (2021), Brunner et al. (2021), and Li et al. (2022).

The resilience motive naturally arises in my framework because firms have the opportunity to adjust the shipments of goods from their different plants to markets in response to realized productivity shocks. Thus, firms can shift production from plants that experienced disruptions to plants that did not. However, the option to switch production across plants is constrained by their initial investments in capacity. Ex-ante, firms have incentives to increase their investment in capacity in their chosen locations to hedge against potential disruptions in their plants.

Plant location and capacity choices are inherently interdependent because plants can be used as export platforms. The firms' plant location and capacity decisions need to be taken jointly rather than independently, which is difficult if the number of potential locations is significant, as in the global car industry. The problem is further complicated because it involves an optimization under uncertainty over a large set of states of the world. Rather than devolving into a large combinatorial discrete choice problem, I demonstrate that in my model, the optimal plant capacity choices are the solutions to a convex optimization problem for which efficient numerical algorithms exist.[5]

The model delivers quantitative predictions about the geography of global production, namely, where plants are located, how large these plants are, where cars are produced, and the flows of vehicles between production locations and markets. Moreover, it provides a tool to evaluate how counterfactual changes in the probability distribution of weather disasters shape the distribution of production across space.[6]

I estimate the model by matching the current geographic distribution of car production. I leverage the structural equations implied by the model to estimate demand parameters and trade costs. I use a simulation-based method of moments to estimate the determinants of productivity and of the cost of investment in capacity for each location.

The main goal of the quantitative model is to evaluate how firms will choose their production locations as the probability of floods increases. I draw upon projections from the Coupled Intercomparison Project Phase 6 (CMIP6) climate models to inform these increases in probabilities in specific regions. Specifically, I measure the likelihood of these negative weather events as the probability of a historical 100-year five-day precipitation event, a proxy for floods, happening in a given location under different Shared Socioeconomic Pathways (SSPs), which capture alternative possible future greenhouse gases emission trajectories, for the period 2035–2064.

Changes in the probabilities of extreme weather events are heterogeneous across space. For instance, in SSP5-8.5, the worst-case business-as-usual emissions scenario considered by the IPCC, the probability of a 100-year five-day precipitation event, which historically is 1% in any given year, is expected to increase in Tennessee to 2.2%, in Michigan to 2.3%, and in Tokyo to 1.4%. By contrast, the probability of such an event in Tangier, Morocco, decreases to 0.8%. On average, in this climate change scenario, 10-year extreme precipitation events and 100-year extreme precipitation events become 1.46 and 1.89 times more likely, respectively.

[5]This is convenient because in convex problems, Karush-Kuhn-Tucker conditions are necessary and sufficient for achieving global optimality.

[6]Generally, this model can be used to study the effect of changes in the probability distributions of the determinants of plant-specific productivities, trade costs, or demand shifters.

In my main counterfactual exercise, I change probabilities from the current flood risk landscape to the probabilities projected by climate change models using the SSP5-8.5 scenario. Then, I recompute plant locations and capacity choices for each firm. In response to the heightened risk, firms produce with more plants, but these plants are smaller. The average firm increases its number of plants by 8.7%, but the average capacity per plant decreases by 9.7%. Firms shrink considerably; on average, production capacity declines by 1.7% and profits by 3.8%. Firms operate with more spare capacity, holding 13.5% of their total capacity for hedging purposes.

These findings reveal two things. First, firms can adapt to an increase in the probability of negative weather events by investing in more plants, thereby reducing their exposure to local disruptions. Second, firms hold more spare capacity in each of their plants to have the option to reallocate production after adverse shocks. This reorganization is costly, as firms shrink while bearing the investment costs of disproportionately large capacity choices to hedge against disruptions.

Geographically, firms increase production and capacity in places close to large markets with relatively smaller probabilities of extreme precipitation events, such as Central Mexico, the West of the United States, Northern Africa, Turkey, the South of India, and the North of Italy. On the other hand, there is a decrease in production in England, the Northeast and the Midwest of the United States, the West part of India, and the Northeast of France. With this reallocation, average productivity declines by 6.8%, and consumer prices, which are a sufficient statistic for the decrease in consumer welfare in the model, increase by 2.6%. Although almost all countries experience an increase in consumer price indices, the incidence is heterogeneous.

Regarding how effective this adaptation is at reducing the losses due to climate change, the average decline in profits is 3.8% when firms reoptimize their plant configuration choices. In contrast, this decline would be 4.7% if firms do not adapt. Leveraging these adaptation channels, automobile firms can avoid approximately 18% of the prospective losses from climate change. However, firm-level adaptation reduces consumer welfare. From the consumers' perspective, the reallocation of plants across space is an aggregate shock as all varieties become more expensive due to the losses in productivity and capacity. When firms do not adapt to climate change, consumer price indices increase, on average, by just 0.7%. This is because disruptions to individual firms are not very costly for consumers in industries with many varieties. Consumers can adapt to idiosyncratic increases in the price of one variety by substituting it for others.

This paper contributes to several strands of the literature. First, it is closely related to the literature that studies the impact of climate change and weather disasters on economic activity. This question has been approached in a number of settings across several fields.[7] This paper is most closely related to the body of literature that has approached this question from an international trade and spatial perspective by studying the impact of climate change on the distribution of economic activity across cities, regions, and countries (e.g., Costinot et al. 2016, Desmet et al.

[7]For instance, Golosov et al. (2014) and Nordhaus (2017) build macroeconomic models to study the effects of climate change at an aggregate level. At a micro-level, papers that have studied the impact of weather disasters on economic activity include Jayachandran (2006), Deschênes and Greenstone (2007), Dell et al. (2012), Hornbeck (2012), Burgess et al. (2017), Albert et al. (2021), and Moscona (2022).

2021, Kocornik-Mina et al. 2020, Cruz and Rossi-Hansberg 2021, Balboni 2021, Desmet and Rossi-Hansberg 2021, Nath 2022, Jia et al. 2022, and Hsiao 2022). This paper contributes novel insights by analyzing, empirically and theoretically, two mechanisms of endogenous potential adaptation that firms can use to lessen the impact of extreme weather events caused by a changing climate: redesigning the spatial organization of their plant network and using their multiplant structure to hedge when one of their plants faces an extreme weather event.

Additionally, this article is closely related to three recent papers, Indaco et al. (2020), Pankratz and Schiller (2021), and Gu and Hale (2022), that explore the effect of climate disasters on the organization of firms' production. Indaco et al. (2020) finds persistent declines in employment and wages in affected businesses, and relocation of establishments to safer neighborhoods in New York City after Hurricane Sandy. Pankratz and Schiller (2021) shows that firms terminate supplier relationship when realized climate shocks exceed expectations, replacing them with others located in places with lower climate risks. Gu and Hale (2022) finds little evidence for an effect of climate-related natural disasters on FDI flows and multinationals affiliate location to climate change, but suggests that responses are increasing over time as the attention to climate change risk grows. My contribution relative to this literature is that, using data from a particular industry, I measure the damages of climate-related extreme events and combine them with a structural model allowing me to understand, through the use of counterfactuals, how an increase in the likelihood of disasters affects the spatial organization of firms.

Third, this paper adds to the large body of work that studies the location decisions of firms in international trade. There are a number of papers that study multinational production, quantitatively or theoretically, such as Brainard (1997), Helpman et al. (2004), Ramondo and Rodríguez-Clare (2013), Ramondo et al. (2013), Antràs and Yeaple (2014), Arkolakis et al. (2018), and, particularly close to this paper, Tintelnot (2017). Most of the quantitative papers in the literature use a probabilistic representation of the firms' problem to build static general equilibrium models with rich geography. This paper studies the joint problem of location and capacity choice that had not been introduced in quantitative multinational models before.[8] Including capacity constraints allows me to provide a general framework for studying quantitatively how changes in the probability distribution of demand or supply shocks affect the firms' optimal plant location decision and how these shocks propagate within their plant network.[9,10] Moreover, this framework allows me to

[8]The implications of capacity constraints or decreasing returns to scale in international trade models have been studied in Vannoorenberghe (2012), Blum et al. (2013), Soderbery (2014), Almunia et al. (2021), and Alfaro-Ureña et al. (2022a). These papers are, either stylized theoretical explorations, or empirical papers, and therefore, do not embed a capacity choice problem or increasing marginal costs in a quantitative model in which firms can set up plants in multiple places and sell to multiple markets.

[9]The addition of capacity constraints implies that there is no closed form solution, and therefore, I focus on an industry equilibrium. Embedding this mechanism in a general equilibrium framework is computationally challenging although feasible if relevant for the specific application.

[10]This paper also builds on the theoretical literature pioneered by Pindyck (1988), Pindyck (1993) and Dixit and Pindyck (1994) that studies real options and characterize the problem of a firm making an irreversible investment in capacity under uncertainty about future output prices or input costs. In the particular context of multinational firms, Rob and Vettas (2003) study, theoretically, the decision of a multinational firm between exporting or opening a foreign facility to serve a foreign market when demand is uncertain. In relation to this work, this paper studies

incorporate resilience in the spatial organization of firms.

The computational approach I introduce is also novel to the literature that quantitatively studies plant and affiliate location problems. The two dominant approaches to studying these problems consist of either choosing for each market, the least cost supplier, but abstracting from fixed costs, making sourcing decisions independent of each other (see Ramondo et al. 2013, Ramondo 2014 or Arkolakis et al. 2018), or including fixed costs, allowing for interdependencies across choices, but creating a high-dimensional, nonconvex problem (see Tintelnot 2017, Arkolakis et al. 2021).[11] Instead, I formulate the firm's plant location and capacity decisions as a convex optimization problem, allowing interdependencies between decisions and preserving computational tractability. Achieving convexity in the capacity choice problem comes at the expense of not having a closed form solution to the problem of organizing production flows from plants to markets conditional on capacity constraints.[12] I demonstrate that this problem is convex as well; specifically, it can be formulated as a linear program defined on a convex set, making it computationally fast. To this end, I borrow techniques from the literature on optimal transport.[13]

Fourth, this paper is related to the literature that studies supply chain resilience and disruptions. Jiang et al. (2021), Grossman et al. (2022) and Baldwin and Freeman (2022) analyze, theoretically, the different incentives for investment in resilience and optimal policy when firms face potential supply chain disruptions. These supply chain disruptions are quantitatively important, as shown by Barrot and Sauvagnat (2016), Boehm et al. (2019), and Carvalho et al. (2020), all of whom leverage natural disasters to study the role of firm-level linkages in propagating input disruptions. I contribute to this literature in two different ways. First, I provide evidence that weather-related extreme events have a direct effect on the affected plants, but also an indirect effect through their propagation within the plant network of a firm. Second, I propose a quantitative framework for studying investment in resilience to disruptions through plant organization in the face of an exogenous increase in risk.

The rest of the paper is structured as follows. In Section 2, I describe the global car production and flood datasets, and document the impact of large floods on production using an event-study design. In Section 3, I present a theoretical model of plant location with capacity constraints. Section 4 describes the estimation strategy of the parameters of the structural model. Section 5 contains different climate change counterfactual exercises. Section 6 concludes.

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the optimal investment in capacity of multinational firms when facing uncertainty about plant productivity in a quantitative setting. In a quantitative setting in the multinational firms literature, Garetto et al. (2021) use a real options framework to study the expansion patterns of multinational enterprises. However, the paper abstains from investigating the case in which plants can be used as export platforms and from capacity investments.

[11] See Antràs et al. (2017), Alfaro-Ureña et al. (2022b), Antràs et al. (2022) and Castro-Vincenzi et al. (2023) for examples of papers that attempt to solve combinatorial problems when the different alternatives are interdependent by leveraging properties of payoff functions in international trade.

[12] Another paper that provides a tractable approach to solving combinatorial plant location problems without solving for discrete decisions is Oberfield et al. (2020). In their approach, they take advantage of insights from discrete geometry to study a tractable limit case of their problem in which cannibalization forces operate locally, and firms decide the optimal catchment area for each plant.

[13] See Villani (2003) for a general treatment of the subject and Galichon (2017) and Fajgelbaum and Schaal (2020) for specific applications to international trade and economic geography.

2 Empirical Evidence

In this section, I estimate the effect that severe floods have on a car plant's production. Using detailed global plant-level production data for the automotive industry around the world for the period between 2000-2019 and comprehensive global data on historical floods since 1985, I find that the occurrence of a large flood centered at most 100km away from a plant causes a sizable, negative and persistent decline in the plant's production. By leveraging information about which car models are produced in which plants, I estimate that plants that are not directly affected by a flood but produce at least one of the models in an affected plant increase their production after one of its sibling plants is treated.

2.1 Data

I use a dataset compiled by IHS Markit of new car registrations that reports quarterly flows of individual models by plant of assembly and country of sale. The dataset covers the period 2000-2019 at a quarterly frequency and contains information for 354 car brands, 77 countries of sale (which I denote henceforth as markets), and 1105 production plants located in 54 countries. In a given quarter, the average firm has three plants. The distribution of plants per firm has a long right tail. The median number of plants per firm is 2, the $90th$ percentile is 7 plants and the maximum is 18. Different versions of this data have been used in previous literature, for instance, in Coşar et al. (2016), and Head and Mayer (2019).

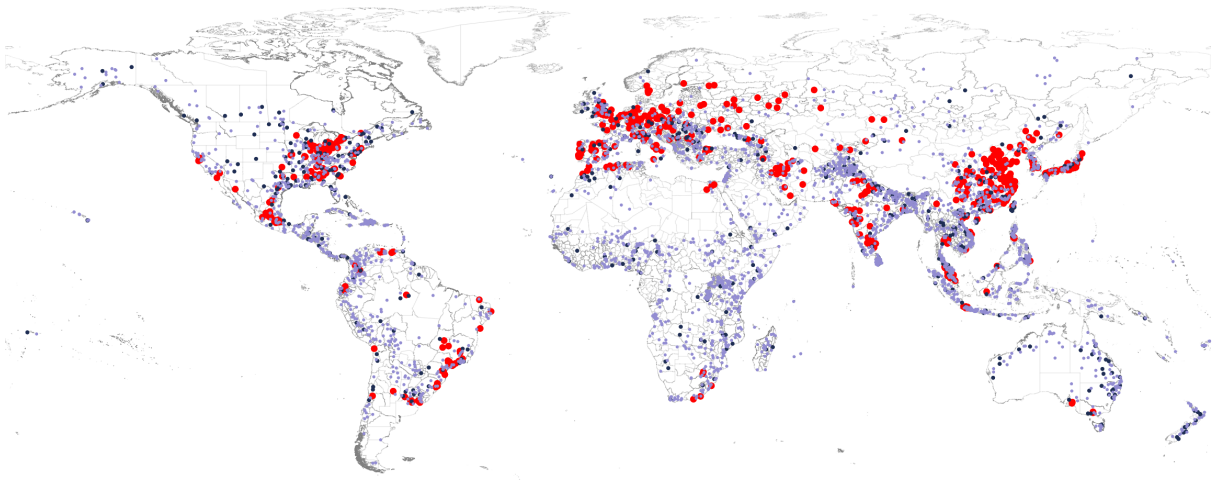
I use the geographical coordinates of the plants to map them to the Global Administrative Unit Layers (GAUL), which are a set of administrative units with global coverage that are consistent across time periods and borders, created and maintained by the Food and Agriculture Organization (FAO).[14] These administrative units have two spatial levels, GAUL1, which corresponds to the first division in the hierarchy within a country administrative organization, e.g states in the United States, and GAUL2, which is the second level in the hierarchy, e.g counties in the United States. Plants are located in 301 GAUL1 units and 554 GAUL2 units.

I obtain information about historical floods from the Dartmouth Flood Observatory (DFO) which uses different sources, such as news, governmental statements, satellite imagery, and remote sensing, to create the Global Archive of Large Flood Events. For each flooding event, the database collects information about estimated dates for the start and the end of the event, the causes of the flood, an estimate of the geographical location and extent of the flood, and a measure of severity. This archive starts in 1985 and is actively maintained.

In Figure 1, I show a map with the global distribution of assembly plants and the location of the floods in the dataset. The map shows that car plants are mostly located in the Midwest of the United States, Western Europe, Eastern China, Japan, and Southeast Asia. It also reveals that, currently, car plants are located in places that experience floods. As can be seen from the map,

[14] More information about the Global Administrative Unit Layers of the FAO can be found in the following website https://data.review.fao.org/map/catalog/srv/api/records/7e6357e6-0893-4b61-a26d-eb09a04eed72.

Figure 1: The Location of Car Production Plants and Floods



Notes: In this map, the red dots correspond to the location of a plant in the car production dataset. The dark blue dots correspond to centroids of 100-year floods that have taken place since 2000. Light blue dots correspond to 10-year floods. The administrative borders in gray correspond to GAUL1 units.

many 100-year floods have happened near car factories. In Table 1, I describe the frequency of flooding events that affect car plants in the DFO. Flooding events are rare, affecting plants in very few periods. Plants are affected by floods in only 2.4% of the quarters—however, 77% of the plants in the sample experience a flood from 2000 to 2019. On average, 1.9 floods occur less than 100km from a plant. By flood severity, the table shows that floods with a recurrence interval of 10 years are more frequent than 100-year floods, as expected. 70% of plants experienced a 10-year flood close to them, but only 25% of the plants are affected by 100-year events.

Table 1: Frequency of Flooding Events that Affect Plants

		Recurrence Interval	
	Floods	**10-year**	**100-year**
Plant-Quarters	2.36%	1.98%	0.41%
Plants	77%	70%	25%
Number of Floods	1.88	1.58	0.32

Notes: This table shows statistics about the frequency and number of flooding events occurring close to car plants. I consider flooding events with a centroid 100 kilometers or less away from car assembly plants 10-year floods have are vents with a recurrence interval of more than 10 years, but less than a 100. 100-year floods have an estimated recurrence interval greater than 100 years.

For most of the empirical analysis, the unit of observation is the production plant and the main outcome is the log of the quantity of cars produced in an assembly plant in a quarter. I define the treatment as the occurrence of a flooding event with a centroid 100 kilometers or less away from a car assembly plant, although the results are robust to different distance thresholds. Also, I use the measures of severity in the dataset to define two types of floods according to the recurrence

interval of the event. The first class includes floods with a reported interval of one or two decades since the last similar event but less than 100 year estimated recurrence interval, and the second type contains very extreme floods with an estimated recurrence interval greater than 100 years. In the following empirical analysis, standard errors are clustered at the GAUL-1 level to capture potential correlation in the error terms across plants located in the same administrative unit and serial correlation over time.

2.2 Estimation Strategy

To estimate the total effect of severe floods on car production, I consider specifications of the following type

$$Y_{i,t} = \eta_i + \eta_t + \sum_{\ell=0}^{K} \gamma_\ell^{i,t} Flood_{i,t-\ell} + u_{i,t}. \tag{1}$$

where $Y_{i,t}$ is the outcome of interest, η_i is a unit fixed effect, η_t is a time fixed effect, $Flood_{i,t-\ell}$ is a binary variable that takes a value of 1 if plant i experienced a flood in period $t-\ell$ and $u_{i,t}$ is the error term. Using this estimating equation, the goal is to estimate average treatment effects, $\gamma_\ell = \mathbb{E}\left[\gamma_\ell^{i,t}\right]$ for $\ell = 0, \ldots, K$. Besides the usual identification assumptions of no anticipation, treatment exogeneity and parallel trends, this research design needs to deal with three empirical concerns. The first concern is related to a data shortcoming; I infer car production in a given plant from registration data, and, therefore, it is difficult to ascertain whether a particular flood is affecting a contemporaneous or a future quarter's inferred production.[15] The other two concerns are related to the characteristics of the treatments. The treatment effects of floods on car production are potentially heterogeneous across plants and periods. Also, these treatments are not-staggered and repeated over time as the same unit might experience more than one treatment event in the sample period.

To address these concerns, I employ the estimator suggested in de Chaisemartin and D'Haultfoeuille (2022a).[16] This is a differences-in-differences estimator of contemporaneous and dynamic treatment effects robust to heterogeneity that allows for the treatment to vary over time. It is given by,

$$DID_{i\ell} = Y_{i,F_i+\ell} - Y_{i,F_i-1} - \sum_{i':F_{i'}>F_i+\ell} \frac{1}{\sum_{i':F_i'>F_i+\ell} 1} \left(Y_{i',F_i+\ell} - Y_{i',F_i-1}\right),$$

[15] According to IHS, the average time between the production of a car and its registration is around three weeks for domestic transactions to two or three quarters for international transactions. However, there is a lot of variation in lead times in the time series depending on demand and supply conditions.

[16] The estimate of γ_ℓ that is retrieved from using lags of the treatment variable, plant and time fixed effects in an OLS regression, the canonical distributed-lag research design, is a sum of $K+1$ terms, even under parallel trends. The first term corresponds to a weighted sum (with possibly negative weights) of the effect of the ℓth treatment lag on the outcome across units for which that treatment lag is equal to 1. This sum might be biased if there are heterogeneous effects across units and periods. The second group of sums are weighted sums of the effects on the outcome of other treatment lags. These effects might contaminate our estimate if these are heterogeneous as well. It is noteworthy that due to this second group of sums, even if there is no anticipation and with parallel trends, the leads of a treatment can show up as being different from 0.

which aggregates into

$$DID_{+,\ell} = \sum_{i:F_i+\ell \leqslant T} \frac{DID_{i\ell}}{N_\ell^1}, \tag{2}$$

where $Y_{i,F_i+\ell}$ corresponds to the outcome of interest for observation i at moment $F_i+\ell$, or ℓ periods after plant i received the treatment for the first time in period F_i. N_ℓ^1 are the number of plants, reaching ℓ periods after their first extreme flood, before or at the end of the sample period T. The idea behind this diff-in-diff estimator is to compare the evolution of the outcome variable for the units that were treated a number of ℓ periods ago with units not-yet treated ℓ periods after each unit's first treatment. The first difference compares the outcome ℓ periods after the plant was treated for the first time with the outcome the period before the unit was treated, and the second difference compares this long difference with the average difference for units that have not yet-been treated by period $F_i + \ell$.[17]

2.3 The Impact of Weather-Related Disasters on Car Production

I start by estimating the effect of the occurrence of a flood close to a plant on the number of cars produced.[18] In Figure 2a, I show the estimates of Equation (2) for the periods between the moment of the first flood up until 40 quarters afterward. As discussed before, in each point ℓ the estimator computes the average effect of being treated for the first time ℓ periods ago. For example, the estimate 30 periods after the first treatment indicates that, on average, log car production is 27% smaller than it would have been if the unit had not been treated. The estimates stabilize around 20 quarters after the first treatment, which allows me to think about the long run effect of severe floods on the number of cars produced in a plant. I compute this long run effect by averaging the point estimates for 20 to 40 quarters after the unit was treated for the first time. In Figure 2a, I show that the long run effect caused by a flood on car production is a reduction in the number of cars produced of about 0.34 log points relative to production in plants that have not been yet treated.

In Figures 2b and 2c, I estimate event studies corresponding to floods that with a 100-year recurrence interval and floods with at least a 10-year recurrence interval, but less than 100-year. As expected, the effect of the most severe floods, the 100-year floods, is sizable and negative. The long run effect of the occurrence of a 100-year flood close to a plant indicates that the most severe floods in the sample reduce car production in 0.69 log points. In the case of floods with a recurrence interval of 10 years or more, the long run effect corresponds to a decrease of 0.28 log points.[19]

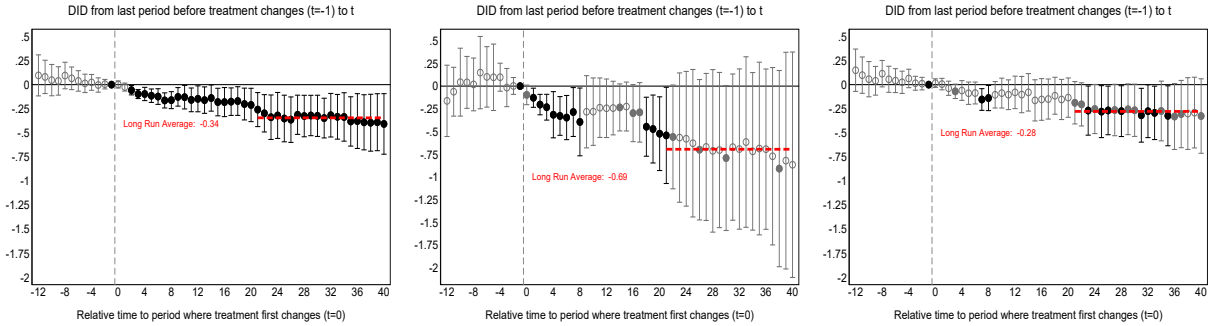
[17] In Appendix C, I describe precisely the assumptions, the parameters and the estimators introduced by de Chaisemartin and D'Haultfoeuille (2022a) in the context of my application.

[18] The sample used to estimate the total effect of floods on car production comprises assembly plants that produce 50 units or more during all the quarters between 2000-2019 and did not experience any flooding events on the 28 quarters before the first period in the sample to avoid mislabeling plants that had already experienced a treatment before the sample as being untreated.

[19] In each case, I compute these estimates by excluding plants that experienced 10-Year floods, when the treatment are 100-year floods, and that experienced 100-year floods, when the treatment are 10-year floods.

Figure 2: The Impact of Severe Floods on Car Production

(a) All Floods (b) 100-Year Floods (c) 10-Year Floods



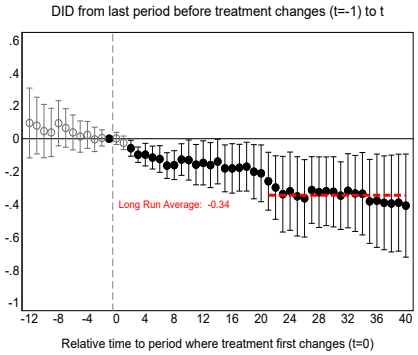
Notes: In these plots, the y-axis shows the values of Equation (2) for the outcome Log Plant Production for 0 to 40 quarters after the plant was flooded for the first time. The pre-trend estimates are computed using placebo estimators as described in Equation (C.8). The sample comprises production plants that produce 50 units or more during all the quarters between 2000-2019 and did not experience any flooding events on the 20 quarters before the first period in the sample. Standard errors are clustered at the GAUL1 administrative level and computed with 100 bootstrap replications. The circles correspond to the point estimate, the bars correspond to 95% confidence intervals and the colors of the circle mean ● significant at 5%, ● at 10%, ○ not significant at 10%.

Having established that extreme floods have a large negative and persistent impact on plant production, I now turn to document that multiplant firms may use their plant configuration to offset the drop in production of a plant affected by an extreme flood by shifting production to other unaffected plants. To demonstrate this, I proceed in steps. I start by using the information on the location of production of specific car models, defined by their brand (i.e. Ford), nameplate (i.e. Focus), and body type (i.e. Sedan), to establish which plants are siblings within a manufacturer. Then, I define a new treatment variable for each plant that identifies whether one of its sibling plants experienced a flood in a particular period. In other words, I determine if a plant is indirectly affected by a flood by dint of producing at least one of the car models manufactured in a directly affected plant. Finally, I estimate Equation (2) on the subsample of plants with at least one sibling, that are active in all the periods of the sample, and do not experience a direct treatment during the sample period or before. Figure 3 reveals that in the long run there is a reallocation of production to other plants that do not experience floods; production increases by around 0.26 log points relative to plants that did not experience any disasters directly or indirectly through the plant network of the firm.

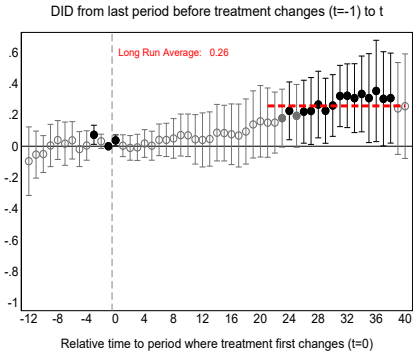
Now, I explore how the occurrence of large floods affect the extensive margin of production. Specifically, I study if experiencing a flood nearby the plant impacts the probability of a plant being active in a given time period. I estimate Equation (2) on the subsample of plants that did not experience any disaster 7 years before the start of the sample. The results of the event-study are in Figure 4a and show that the probability that a particular plant is active declines after a particular plant experiences a flood. The decrease in the probability that a given plant is active after an extreme flood reflects that firms exit more after being treated or that fewer plants are

Figure 3: The Impact of Severe Floods on Unaffected Plants

(a) Direct Effect



(b) Indirect Effect



Notes: In this plot, the y-axis shows the values of Equation (2) for the outcome Log Plant Production for 0 to 40 quarters after a related plant was flooded for the first time. The pre-trend estimates are computed using placebo estimators as described in Equation (C.8). Panel (a), is the same plot as Figure 2a. In Panel (b), The sample comprises production plants that produce 50 units or more during all the quarters between 2000-2019 and did not experience any flooding events during the sample period or on the 20 quarters before the first period in the sample. Standard errors are clustered at the GAUL1 administrative level and computed with 100 bootstrap replications. The circles correspond to the point estimate, the bars correspond to 95% confidence intervals and the colors of the circle mean ● significant at 5%, ● at 10%, ○ not significant at 10%.

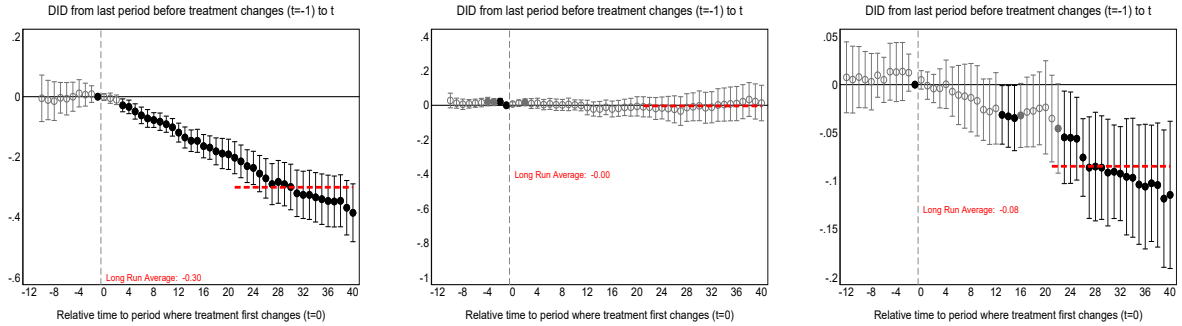
opened in locations that experience floods in the sample period. This result could be explained by the direct effect of the disaster, through deteriorated facilities, infrastructure or increases in production costs, or by an effect on beliefs, as the occurrence of the flood might reveal information about the likelihood that such a disaster will happen again in the future (see Hsiang 2016). In Figure 4b I explore whether large floods induce exit. To do this, I replicate the exercise in Figure 4a, but conditioning on plants that were active in the first period of the sample. The event study shows that experiencing a large flood does not induce plant exit. These suggests that the results in Figure 4a are not driven by exit, but by entry. In Figure 4c, I change my unit of observation to GAUL2 regions to document that the number of plants in a location decreases after a location experiences a flood. More precisely, this event study indicates that in the long run, the number of plants in a location declines by 0.08 log points relative to locations that have not been treated yet.

2.4 Other Outcomes

Now, I turn to the effect of floods on other outcomes related to the organization of production. First, I decompose produced quantities in Figure 2 into the extensive margin of the log number of models in a plant and an intensive margin of the log of the average production per model. I present the results for this decomposition for the three definitions of treatments in Figure D.1 in the Appendix. Two robust patterns emerge. First, there is a large short-run decline of around 20% in production per model for two or three years for the less severe floods. In the case of 100-year floods, the effect of floods on the intensive margin is long-lasting, reducing production by as much as 75% several years after the treatment. Second, there is a long-run reallocation of production capacity away from the affected plants. I find a reduction in the number of models produced in a

Figure 4: The Impact of Severe Floods on the Extensive Margin of Plant Location

(a) Probability of Operating (b) Exit Probability (c) Number of Plants in a Location



Notes: In these plots, the y-axis shows the values of Equation (2) for the outcome Log Plant Production for 0 to 40 quarters after the plant was flooded for the first time in Panel (a) and Log Number of Plants in a GAUL2 location for 0 to 40 quarters after the location experienced a flood for the first time. The pre-trend estimates are computed using placebo estimators as described in Equation (C.8). The sample comprises production plants that were active in did not experience any flooding events on the 20 quarters before the first period in the sample. Standard errors are clustered at the GAUL1 administrative level and computed with 100 bootstrap replications. The circles correspond to the point estimate, the bars correspond to 95% confidence intervals and the colors of the circle mean ● significant at 5%, ● at 10%, ○ not significant at 10%.

plant of 28%.

Also, I analyze the effect of a flood on the total production of a treated firm. Figure D.2 in the Appendix shows the results. Experiencing a flood in one plant reduces total production of the manufacturer by approximately 15% during the first two years after the flooding event, suggesting that production disruptions in individual plants due to extreme floods have a negative impact on firms' aggregate activities.

2.5 Robustness

One concern with the estimates above is that the treatment effects captured in Figure 2 could be the result of spillovers between the treatment and control groups, in a clear violation to the Stable Unit Treatment Value Assumption (SUTVA). In my estimation setting, the potential spillovers are observed and I can control for them. To do this, I control for floods experienced by other plants within the same firm that produce car models with the same platform, using the estimator proposed in de Chaisemartin and D'Haultfoeuille (2022b).[20] In Figure D.3 in the Appendix, I present the results. The values for these estimates are qualitatively and quantitatively similar as the ones depicted in Figure 2.

Another concern is that the distance threshold of 100km to define the treatment is not correctly capturing the effect of floods on the number of cars produced in a plant. In Figure D.4 of the Appendix, I compute the estimator in Equation (2) that produces Figure 2a, but define the

[20]Production lines within plants are not perfectly substitutable between car models. In most cases, these production lines specialize in producing cars within the same platform as mixed assembly lines cause efficiency losses because of different cycle times and equipment adjustments (see Markus 2021). A platform is a shared set of common design, engineering, and components for distinct car models.

thresholds at 25km, 50km, 75km, 150km, 200km, 250km and 300km. In the cases that I decrease the threshold, the long run averages and the dynamics in these plots are similar to the baseline figure. However, the confidence intervals are somewhat larger, reflecting the fact that as I reduce the thresholds the number of treatments declines rapidly. On the other hand, as I increase the threshold the effect of floods becomes closer to 0 both in the short and the long run. These findings provide evidence that floods affect car production through local direct and indirect disruptions.

Finally, one can be worried that the results in Figure 2 might be affected by plants in different countries being affected by country-specific fixed effects. To take this into account, I estimate Equation (2) using a weighted average that compares treated and not-yet treated plants within the same country. These estimators are unbiased even if countries experience differential trends, as long as all plants within the same country experience parallel trends. I present these estimate in Figure D.5 in the Appendix.

3 Quantitative Model

In this section, I present a model of optimal plant location under uncertainty and capacity constraints. In the model, firms choose where to set up their assembly plants, among a set of locations, and invest in production capacity in each of those locations. Firms are, potentially, multinational and multiplant, and have the possibility to use their plants as export platforms (as in Helpman et al. 2004 and Tintelnot 2017). Firms choose their horizontal spatial production organization to maximize expected profits before extreme weather disruptions occur. Thus, at the time of their capacity decision, firms do not know the actual productivity of each potential plant location, just the location-specific probability distributions of these productivities. After the weather events are realized, firms choose production flows from each of their plants to final markets, conditional on a capacity constraint for each potential location.

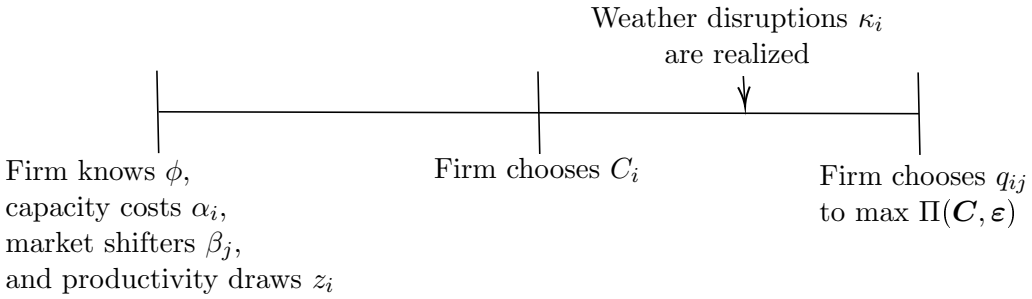
3.1 Setup

I model the problem of firm n headquartered in country h_n, with quality equal to γ_n and fundamental productivity equal to ϕ_n. The firm is the sole owner of a blueprint to produce a single differentiated variety of a good. It needs to choose in which locations to erect its plants in order to serve multiple final markets. I index plant locations by $i = 1, \ldots, I$ and markets by $j = 1, \ldots, J$.

The model is static and the firm makes decisions in two stages. The timeline of events is depicted in Figure 5. At the beginning of the first stage, firm n knows the value of the triplet of its fundamentals, $\{h_n, \gamma_n, \phi_n\}$, the costs of building capacity in each location, $\{\alpha_{in}\}_{i=1}^{I}$, the market-specific demand shifters, $\{\beta_{jn}\}_{j=1}^{J}$, and a vector of firm-location potential plant productivities, $\{z_{in}\}_{i=1}^{I}$. With this information at hand, the firm makes one or more sunk, irreversible investments in productive capacity in different locations. After these investments are incurred, a vector $\{\kappa_{in}\}_{i=1}^{I}$ of weather-related shocks that determine the actual productivities of all of its plants is realized. Finally, the firm chooses its production plan conditional on the available capacity at each location

and the productivity of each plant. This amounts to choosing shipments of goods from each plant to each market q_{ij} that maximize profits and respect the capacity constraints.

Figure 5: Timeline of the Model



Geography features in the model in different ways. First, there are bilateral iceberg trade costs that firms have to pay to ship cars internationally. Second, production locations are heterogeneous in their average productivity, average capacity costs, and in the probability of experiencing floods. Finally, the costs of investing in capacity and the productivity of a plant depend on the location of the plant and how far this location is from the firms' headquarters.

3.2 Demand Function and Market Structure

In each market j, a mass of homogeneous consumers L_j demand both cars and other goods. Consumer preferences are given by

$$U_j(Q_C, Q_O) = Q_C^{\alpha_j} Q_O^{1-\alpha_j}, \tag{3}$$

which implies that a share α_j of expenditure is devoted to consumption of cars and a share $1-\alpha_j$ to other goods. Consumers have preferences over a measure of differentiated car varieties indexed by ω which are valued using a constant elasticity of substitution aggregator with elasticity of demand equal to $\sigma > 1$,[21]

$$Q_C = \left(\int_{\omega \in \Omega_j} (\psi_j(\omega) q_j(\omega))^{\frac{\sigma-1}{\sigma}} d\omega \right)^{\frac{\sigma}{\sigma-1}}, \tag{4}$$

where Ω_j is the set of available varieties in market j and $\psi_j(\omega)$ is a demand shifter specific to variety ω and market j. This demand shifter combines two components; the brand-specific quality γ_n and a home market effect. Notice that I assume that consumers do not distinguish goods of the same variety produced in different origins. With these preferences, the demand for variety ω in market j is

[21] This utility for the representative agent can be by a population of consumers in a country behaving according to a logit discrete choice model à la Anderson et al. (1988).

$$q_j(\omega) = p_j(\omega)^{-\sigma} \underbrace{\psi_j(\omega) R_j P_j^{\sigma-1}}_{\equiv \beta_j(\omega)^\sigma}, \tag{5}$$

where $p_j(\omega)$ is the price of variety ω in country j, R_j is total expenditure in cars in market j, and P_j is the ideal price index given by

$$P_j = \left(\int_{\omega \in \Omega_j} \left(\frac{p_j(\omega)}{\psi_j(\omega)} \right)^{1-\sigma} d\omega \right)^{\frac{1}{1-\sigma}}. \tag{6}$$

I summarize total expenditure, the ideal price index, and the demand shifter in a single variable $\beta_j(\omega)$ that measures the size of market j for variety ω. Each good ω is produced by a single firm n under monopolistic competition.

The other consumption good Q_O is homogeneous, freely tradable, and I assume that its consumption is large enough so that it is produced in every single country. This good will be the numeraire of the model and allows me to pin down wages, w_j, which are the price of labor, the only factor of production in this economy. Aggregate income is then given by $Y_j = w_j L_j$ units of the outside good. These assumptions imply that the only aggregate variable that must be solved in the industry equilibrium is the price index, P_j.[22]

3.3 Production Technology

A firm can produce its variety in a set of I locations indexed by $i = 1, \ldots, I$. Each plant can then be used to serve the markets where it is located and as an export platform. A firm that establishes a plant in a given location makes a sunk irreversible investment in capacity, which determines the maximum number of units of the good the firm can produce in that location.

The production function for each plant is linear in its labor input which is the only factor of production, but the total quantity produced is subject to a capacity constraint. That is,

$$Q_{in} = \underbrace{\kappa_{in} \phi_n z_{in}}_{\equiv \varepsilon_{in}} L_{in} \quad \text{s.t} \quad Q_{in} \leqslant C_{in}. \tag{7}$$

where Q_{in} denotes the total number of cars produced by firm n in location i and ε_{in} is defined to be the *ex-post* productivity of firm n in that location. Productivity is the product of three variables: firm n's fundamental productivity ϕ_n, a local productivity z_{in}, both known by the firm at the time of making the capacity investment decision, and a weather disaster, κ_{in}, that is unknown to the firm at the time of choosing its capacity. The weather disasters follow a discrete probability distribution

[22] This formulation for closing the model and focusing on the industry equilibrium implies that the only aggregate variables that need to be solved are the ideal price indices, P_j, in each country.

$$\kappa_i(\omega) = \begin{cases} \kappa_1 & \text{with probability } r_i \\ \kappa_2 & \text{with probability } s_i \\ 1 & \text{with probability } 1 - r_i - s_i, \end{cases}$$

with $\kappa_1 < \kappa_2 < 1$ and $r_i < s_i$. Event 1 is more severe than Event 2, but it is less frequent. This modeling of the weather shocks aims to reproduce to the 10- and 100-year flooding events explored in Section 2. Probabilities are potentially heterogeneous across locations i. The main counterfactual exercise in this paper consists of changing the probabilities of the flooding events r_i and s_i in line with projections associated with different climate change scenarios.[23]

Since facilities in each location can be used as export platforms, the firm's total production in a given location is the sum of the shipments of that facility to all the potential final markets. Trade of automobiles across space is costly. In order to ship one car from country i to country j, firms need to produce $\tau_{ij} \geqslant 1$ units of the good. Therefore, total production in a plant can be written in terms of the shipments of goods between that production facility and final markets as,

$$Q_{in} = \sum_{j=1}^{J} \tau_{ij} q_{ijn}, \tag{8}$$

where q_{ijn} is the number of cars that arrive to market j, produced in location i by firm n.

Building capacity in a location is costly. Firms need to make an irreversible investment to be able to produce at most C_{in} cars in location i equal to $f_{in}(C_{in})$. The capacity cost function is heterogeneous across locations and firms, capturing the notion that the cost of building a facility might depend on the cost of land and labor in a particular location, and standard gravity variables such as the distance between the firms' headquarters and a location.

I assume $f_{in}(C_{in})$ satisfies three conditions. First, this function is weakly positive, $f_{in}(C_{in}) \geqslant 0$ for $C_{in} \geqslant 0$. Second, it is strictly increasing in capacity, $f'_{in}(C_{in}) > 0$ for all i, n and $C_{in} \geqslant 0$. This assumption is relevant because making the marginal cost of the first infinitesimal capacity unit strictly positive, $f'_{in}(0) > 0$, is what allows the model to generate zero investment in some locations. Third, I assume that the investment function is weakly convex, $f''_{in}(C_{in}) \geqslant 0$ for all i, n and $C_{in} \geqslant 0$. In the quantitative application of the model, I assume for simplicity that the function $f_{in}(C_{in})$ is linear with marginal cost α_{in}, i.e., $f_{in}(C_{in}) = \alpha_{in} C_{in}$.

3.4 The Firm's Problem

The goal of the firm is to choose a production capacity in every production location to maximize its expected profits net of the investments incurred in capacity costs. The decision of where to

[23] The reason I model extreme weather events using this particular three-point discrete distribution is that it provides a clear mapping between the historical data on floods in Section 2, the model, and the extreme event projections provided by most climate models used in the counterfactuals in Section 5. However, any distributional assumption for the shocks can be chosen for the model as in the solution algorithm that I present in Section 3.5 I use simulations to approximate the value of expected profits given a value of capacity. In fact, the distribution of *ex-post* shocks could be continuous and draws could be spatially correlated.

invest and how much is taken before the actual values of the firm-location specific weather shocks are realized, but with knowledge of their respective distributions. Firms have rational expectations about the weather shocks and maximize expected profits.

Proceeding by backwards induction, I start by describing the problem for firm n conditional on a vector of capacities, $\boldsymbol{C_n} = \{C_{in}\}_{i=1}^{I}$, and location productivities, $\boldsymbol{\varepsilon_n} = \{\varepsilon_{in}\}_{i=1}^{I}$. Then I examine the problem of choosing the vector of capacities *ex-ante*, given the solution of the *ex-post* problem. The *ex-post* optimization problem of firm n conditional on a vector of capacities $\boldsymbol{C_n}$ and location productivities $\boldsymbol{\varepsilon_n}$ is

$$\Pi_n(\boldsymbol{C_n}, \boldsymbol{\varepsilon_n}) \equiv \max_{q_{ijn} \geqslant 0} \sum_{j=1}^{J} \beta_{jn} \left(\sum_{i=1}^{I} q_{ijn} \right)^{\frac{\sigma-1}{\sigma}} - \sum_{j=1}^{J} \sum_{i=1}^{I} \frac{\tau_{ij} w_i}{\varepsilon_{in}} q_{ijn} \tag{9}$$
$$\text{s.t} \quad \sum_{j=1}^{J} \tau_{ij} q_{ijn} \leqslant C_{in} \quad \forall i \quad [\nu_{in}] .$$

This maximization combines an optimal flow problem, in which a monopolistically-competitive firm facing an isoelastic demand has to select both the quantity supplied and the production sources to serve each final market, with a capacity constraint in each potential source facility. The first term in the profit function corresponds to the sum of revenues in every market. Notice that these revenues depend on the total quantity supplied to a market regardless of the source of the good. This is because, by assumption, goods of the same variety produced in different origins are perfect substitutes. The second term captures total production costs. Costs are linear in the quantities produced, while the marginal cost of producing a unit in location i and selling it in market j depends on the wage, w_i, divided by firm n's productivity in that location, ε_{in}, and the iceberg trade cost, τ_{ij}. Then, for each potential production location there is a capacity constraint that restricts the amount of goods, inclusive of trade costs, produced in a plant. The variable ν_{in} denotes the Lagrange multiplier associated with the capacity constraint in location i for firm n.

It is worth delving into the role that the variable ν_{in} plays. Mathematically, if and only if this multiplier, ν_{in}, is positive, the capacity constraint associated with C_{in} is binding. Economically, ν_{in} quantifies the increase in profits from increasing C_{in} marginally, i.e., the shadow value of additional capacity in that plant. However, this multiplier has another interpretation. It measures the opportunity cost of producing goods in a plant with a binding capacity constraint. This is because serving a market from a particular plant takes away useful capacity for some other markets.

The profit-maximizing quantity and price in market j are given by

$$Q_{jn} = \beta_{jn}^{\sigma} \left(\frac{\sigma - 1}{\sigma} \right)^{\sigma} \left(\min_i \left\{ \tau_{ij} \left(\frac{w_i}{\varepsilon_{in}} + \nu_{in} \right) \right\} \right)^{-\sigma}, \tag{10}$$

$$p_{jn} = \frac{\sigma}{\sigma - 1} \left(\min_i \left\{ \tau_{ij} \left(\frac{w_i}{\varepsilon_{in}} + \nu_{in} \right) \right\} \right). \tag{11}$$

Firms optimally serve each market from the plant that can serve that destination at the cheapest

total cost. The cost of supplying a market depends on both the cost of transporting the good from an origin plant to a destination market and on the marginal production cost in that origin plant. Note that the marginal cost is augmented by ν_{in} to reflect the true cost of producing an additional unit in plant i.[24]

Notice that the problem outlined in Equation (9) is a maximization of a concave objective function on a set of linear constraints and, consequently, admits strong duality.[25] Thus, I introduce the dual problem for firm n,[26]

Proposition 1 *The dual ex-post optimization problem of firm n conditional on a vector of capacities* $\boldsymbol{C_n}$ *and location productivities* $\boldsymbol{\varepsilon_n}$ *is*

$$\min_{\nu_{in}\geqslant 0} \sum_{i=1}^{I} \nu_{in} C_{in} + \frac{\left(\frac{\sigma-1}{\sigma}\right)^{\sigma-1}}{\sigma} \sum_{j=1}^{J} \beta_{jn}^{\sigma} \left(\min_{i} \left\{ \tau_{ij} \left(\frac{w_i}{\varepsilon_{in}} + \nu_{in} \right) \right\} \right)^{1-\sigma} \tag{12}$$

Proof *See Appendix E.*

Following Balinski and Baumol (1968), this dual problem has the following economic interpretation. The first term corresponds to the marginal evaluation of the firm's scarce capacity in all of its plants. The second term captures, at the optimal quantities, the difference between the firm's profits and the cost of the units of capacity valued at their marginal contribution.[27] Therefore, this term can be interpreted as the economic rents appropriated by the owner of the blueprint required to produce the variety.

By strong duality, the optimal value attained by the dual problem coincides with the primal *ex-post* problem. Computationally, the advantage of using the dual problem is that I only need to find the values of I multipliers rather than $I \times J$ quantities. Using the dual has the additional

[24] In this model, it is possible that a particular market j is served by more than one plant. This can happen if the capacity constraint binds for some of them. If this is the case, the marginal cost of serving market j must be the same from all of these plants and equal to the production cost of the worst supplier serving that market. The Lagrange multipliers of these plants adjust in order to equalize marginal costs.

[25] Strong duality follows from the convexity of the optimization problem and the linearity of the constraints. Due to these two properties, Slater's conditions holds which is a sufficient condition for strong duality. For an extensive discussion of duality in convex optimization problems see Boyd and Vandenberghe (2004).

[26] The study of dual nonlinear programming problems in economic applications can be traced back to Balinski and Baumol (1968). The authors show that if the entire primal problem is characterized by diminishing returns, which in this problem comes from the concavity of the profit function with respect to quantities, the standard dual properties apply.

[27] Assume the solutions to the primal problem, q_{ijn}, have been assigned to their optimal values. The dual function in Equation (12) is equivalent to

$$\sum_{j=1}^{J} \left[\beta_{jn} \left(\sum_{i=1}^{I} q_{ijn} \right)^{\frac{\sigma-1}{\sigma}} - \sum_{i=1}^{I} \frac{\tau_{ij} w_i}{\varepsilon_{in}} q_{ijn} \right] + \sum_{i=1}^{I} \nu_{in} \left(C_{in} - \sum_{j=1}^{J} \tau_{ij} q_{ijn} \right).$$

The first term corresponds to the optimal profits and can be treated as a constant. The second term corresponds to the sum of unused capacities valued at a cost of ν_{in}. An alternative interpretation is that the dual minimizes the value of the spare capacity. Notice that if in the optimal solution there is excess capacity in every plant, then $\nu_{in} = 0$ for all i and hence the value of the dual entirely corresponds to profits.

advantage that the vector of multipliers that minimizes it is unique, whereas, in the primal problem, the uniqueness of the optimizer is not warranted.

The problem described in Proposition 1 is not easily implementable numerically as it is nonlinear and not continuously differentiable. However, as I show in the next proposition, with a change of variables, the problem can be reformulated into a convex problem with a linear objective function for which efficient optimization algorithms exist.

Proposition 2 *The dual optimization problem described in Proposition 1 can be written as the minimization of a linear objective function on a convex set as*

$$\begin{aligned} \min_{\nu_{in}\geqslant 0,\mu_{jn}>0,t_{jn}>0} & \sum_{i=1}^{I} \nu_{in} C_{in} + \frac{\left(\frac{\sigma-1}{\sigma}\right)^{\sigma-1}}{\sigma} \sum_{j=1}^{J} \beta_{jn}^{\sigma} t_{jn} \\ s.t \;\; & \mu_{jn} \leqslant \tau_{ij} \left(\frac{w_i}{\varepsilon_{in}} + \nu_{in} \right) \quad \forall i,j \\ & (t_{jn}, \mu_{nj}, 1) \in P_3^{\frac{1}{\sigma},1-\frac{1}{\sigma}} \quad \forall j \end{aligned} \tag{13}$$

where $P_3^{\frac{1}{\sigma},1-\frac{1}{\sigma}}$ *denotes a three-dimensional power cone.*[28]

Proof *See Appendix E.*

The problem in Equation (13) belongs to the class of conic optimization programs, a nonlinear extension of conventional Linear Programming optimization problems, for which there are efficient algorithms that can be solved in polynomial-time and a well-developed duality theory (Letchford and Parkes 2018).[29] State-of-the-art software packages such as `Mosek` have streamlined optimization routines that solve conic optimization problems with hundreds of variables and constraints in less than a second.

Given the *ex-post* problem and an efficient strategy to solve it, I am ready to address the *ex-ante* capacity choice problem of the firm. In this problem, firm n chooses the location and the capacity of its production plants to maximize expected profits net of investment costs. It is given by

$$\max_{C_{in}\geqslant 0} \;\; \mathbb{E}_{\boldsymbol{\varepsilon_n}} \left[\Pi_n(\boldsymbol{C_n}, \boldsymbol{\varepsilon_n}) \right] - \sum_{i=1}^{I} f_{in}(C_{in}). \tag{14}$$

The first term in this expression corresponds to the expected operating profits when the vector of capacities is equal to $\boldsymbol{C_n}$. The second term denotes the total investment cost of the installed

[28] A three-dimensional power cone is a convex set defined as $P_3^{\alpha,1-\alpha} = \left\{ x \in \mathbb{R}^3 : x_1^{\alpha} x_2^{1-\alpha} \geqslant |x_3|, x_1, x_2 \geqslant 0 \right\}$.

[29] In general, a *linear conic program on* K is defined as the following optimization program,

$$\min_x \left\{ c^T x : Ax - b \in K \right\},$$

where $K \subset R^m$ is convex, pointed, closed, and with a nonempty interior cone (see Nemirovski 2007)

capacity. I show that this maximization is a convex optimization problem in the following proposition.

Proposition 3 *The* ex-ante *capacity choice optimization problem of the firm is a concave objective function defined on a set of linear constraints.*

Proof *See Appendix E.*

From the envelope theorem, the first order condition for the variable C_{in} is given by

$$\mathbb{E}_{\boldsymbol{\varepsilon_n}}\left[\nu_{in}(\boldsymbol{C_n}, \boldsymbol{\varepsilon_n})\right] \leqslant f'_{in}(C_{in}), \tag{15}$$

with equality if firm n builds a plant in location i, i.e., $C_{in} > 0$. A firm will invest in capacity in location i until the expected marginal increase in profits due to an increase in capacity equals the marginal investment cost of that additional unit.

In addition, this expression highlights that in the optimal vector of plant capacities there is no wasteful investment. If a firm decides to build a plant in a particular location, it must be the case that the capacity constraint binds, since this means that $\nu_{in}(\boldsymbol{C_n}, \boldsymbol{\varepsilon_n}) > 0$, in a non-zero measure of states of the world. In other words, even if *ex-post*, for some particular realization of $\boldsymbol{\varepsilon_n}$ a plant might be producing with spare capacity, *ex-ante*, a rational, profit maximizing, risk neutral firm does not have incentives to build a plant designed to have spare capacity in every state of the world, the plant must be producing at capacity for some productivity realizations.

This optimality condition also elucidates under which circumstances the firm does not set up a plant in some location. This occurs if the expected marginal benefit from investing an infinitesimal amount in location i, with optimal capacities elsewhere, is strictly smaller than the marginal cost of investment at 0, $f'_{in}(0) > 0$.

Lastly, these first-order conditions help understand the incentives to invest in resilience. When a flood affects plant i, ν_{in} decreases; as the plant becomes less productive, and thus, the marginal contribution to profits of its capacity declines. At the same time, the multipliers for all the unaffected plants weakly increase. When the profitability in location i declines, the firm has larger incentives to produce elsewhere. Thus, when the probability of disruptions in location i rises, all else equal, events with a smaller value of the multiplier become more frequent. This decreases the expected marginal return of an additional unit of capacity in i, and then, capacity must decrease to restore the equality in Equation (15). At the same time, capacity investment in all other locations weakly increases as states of the world in which the marginal contribution of capacity in other locations is larger become likelier.[30]

3.5 Solution Algorithm

The model I have described is computationally challenging to solve. There are three reasons for this complexity. First, since plants can serve as export platforms, the investment decisions are

[30] See Propositions 4 and 5 in Appendix E for a formal treatment of these statements.

interdependent across locations. Second, there are no closed form solutions for the *ex-post* flow problem, or for the expectation in the *ex-ante* problem. Third, the dimensionality of the problem is large. However, the convexity of the problem, proved in Propositions 2 and 3, guarantee its numerical tractability.

Since the problem is convex, any locally optimal point is also globally optimal. The Karush-Kuhn-Tucker (KKT) conditions are both necessary and sufficient for global optimality which allows me to leverage large-scale convex optimization algorithms that solve directly for the KKT conditions, and are guaranteed to converge to the unique global optimum (Boyd and Vandenberghe 2004).

Proposition 2 is convenient to compute the expectation in the *ex-ante* problem. Given that the *ex-post* problem can be written as a linear program on a convex set, it can be solved efficiently. For a given value for the vector of capacities and for a vector of productivities, it is easy to compute the vector of multipliers, $\boldsymbol{\nu_n}(\boldsymbol{C_n}, \boldsymbol{\varepsilon_n})$, and the optimal value of the objective function, $\Pi_n(\boldsymbol{C_n}, \boldsymbol{\varepsilon_n})$, from the linear formulation of dual *ex-post* problem. The fact that the solution to this problem is sufficiently fast allows me to overcome the challenge of computing the high-dimensional expectation by approximating it using simulations.

Precisely, given a vector of capacities $\boldsymbol{C}_n$, I compute expected profits and expected multipliers averaging over $s = 1, \ldots, S$ simulation draws,

$$\mathbb{E}_{\boldsymbol{\varepsilon_n}}\left[\Pi_n(\boldsymbol{C_n}, \boldsymbol{\varepsilon_n})\right] \approx \frac{1}{S}\sum_{s=1}^{S} \Pi_n(\boldsymbol{C}_n, \boldsymbol{\varepsilon}_n^{\boldsymbol{s}}), \qquad \mathbb{E}_{\boldsymbol{\varepsilon_n}}\left[\nu_{in}(\boldsymbol{C_n}, \boldsymbol{\varepsilon_n})\right] \approx \frac{1}{S}\sum_{s=1}^{S} \nu_{in}(\boldsymbol{C}_n, \boldsymbol{\varepsilon}_{\boldsymbol{n}}^{\boldsymbol{s}}).$$

Then, I leverage Proposition 3 to use efficient gradient-based optimizers that exploit the convexity of the problem and that the model provides explicit gradients in Equation (15) to find the global optimum.

4 Empirical Results

In this section, I describe, first, the data used estimating the model, then the parameters of the model that I need to estimate, the estimation strategy, and, finally, the estimates of those parameters and their quantitative implications. The goal is to find estimates that reproduce the geographic distribution of car production across the globe and the values for the decline in a plant's productivity caused by floods that rationalize the empirical findings of Section 2.

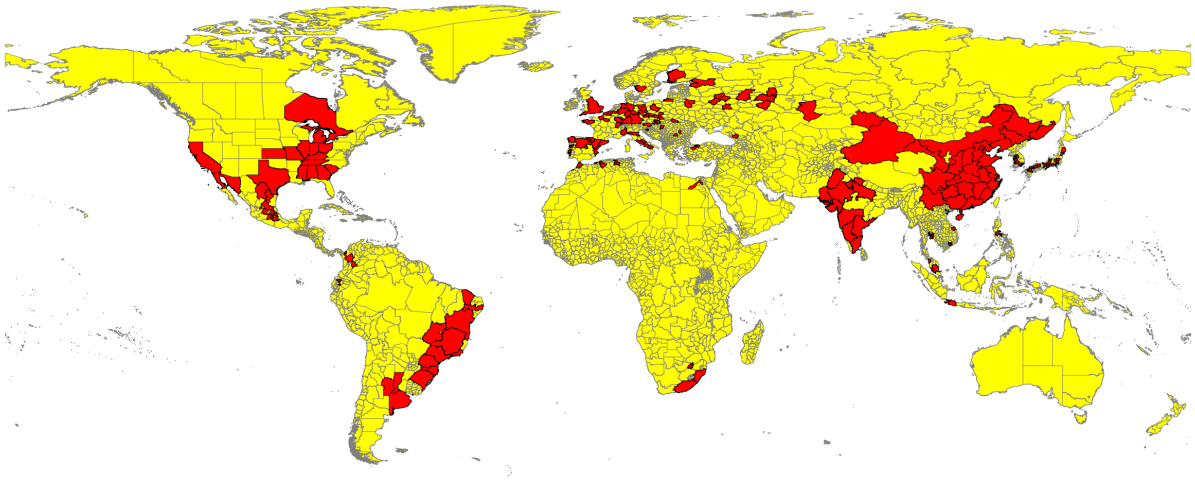
4.1 Structural Estimation Data

I use three types of data. First, I use the car registration dataset described in Section 2. Since the model is static and the computational burden of solving the model is considerable, in the structural estimation, I aggregate the data at an annual level and I use 2019, the last year in the sample. For each plant, I construct flows to each destination market.

I complement the car registration data with list price data (MSRPs) in 2018 and 2019 for a subset of countries, namely China, Brazil, Germany, Mexico, Japan, India and the United States, at the car model level. To these price data, I merge the location where the car models were produced to estimate trade costs. I use this dataset to estimate the demand block of the structural model, by adding bilateral applied tariffs for each pair of countries sourced from the Market Access Map database constructed by ITC (2022), and standard bilateral gravity measures from CEPII (Mayer and Zignago 2011).

In order to estimate the model, I need to define the geographical units at which firms make their choices. Firms' choices need to be made at subnational units of aggregation, as different regions within countries are affected in very dissimilar ways by climate change. I define these subnational units using the Global Administrative Unit Layers (GAUL) constructed by the Food and Agriculture Organization (FAO), which standardize administrative units for all the countries in the world. To maintain computational feasibility, I use GAUL1 units, which are akin to states in the US or NUTS1 in the European Union. The locations included in the estimation of the model appear in red in Figure 6, and correspond to locations where cars were produced in 2019.[31]

Figure 6: Locations Included in the Estimation



Notes: Regions in red are included in the estimation of the model. These are the regions where at least one plant is located in 2019 in the car registration dataset. The administrative units correspond to GAUL1 units.

For each geographical unit, I collect a number of variables that proxy for the local fundamental productivity and the local cost of investment in capacity. I source population counts in 2020 for each 1km grid from the WorldPop project (WorldPop 2021). From Kummu et al. (2018), I retrieve estimates of gross domestic product per capita based on purchasing power parity at a 5 arc-min resolution for 2015. I construct measures of road density using data from Meijer et al. (2018) by averaging highway and primary road density for each cell. As a proxy for the price of land

[31] In the counterfactuals in Section 5, I expand the locations in the firms' choice set to all the GAUL1 units in the countries for which there are sales. In the context of climate change, this is important as firms might start producing in new regions that are less affected by the increase in the likelihood of extreme weather events. These locations are colored in red in Figure B.2 in the Appendix.

in each administrative unit, I construct measures of land availability. Following Saiz (2010), I define land availability in a given region as the share of undeveloped land, i.e., excluding buildings and croplands, with a slope smaller than 15%. I obtain information about global land use from the WorldCover project of the European Space Agency (Zanaga et al. 2021). Finally, I use the geographical coordinates of the centroid of each location to compute *as the crow flies* bilateral distances to the centroid of each country.[32]

4.2 Econometric Specification and Estimation Strategy

I need to estimate trade costs, τ_{ij}, between each location i and market j, the parameters of the demand side of the model, specifically, the elasticity of demand σ, firm-specific qualities γ_n, and firm-market-specific demand shifters, β_{jn}. Then, I need to estimate the parameters that govern the productivities and investments costs in each location, which I treat as structural errors since I cannot recover them directly from the data. I specify probability distributions for the firm location- and firm-specific productivities, and the investment cost in capacity, and estimate the parameters that govern those distributions. Finally, I estimate the values of the productivity penalties from experiencing a flood, κ_1 and κ_2, to replicate the decline in units produced caused by severe floods that I estimated in Section 2.3.

To estimate these parameters, I proceed in two steps. Since estimating parameters using a simulation-based method is computationally expensive, I estimate trade costs and the demand-side parameters using the model-implied pricing and demand equations, and leave the estimation of the parameters of the distributions of the structural errors to a simulated method of moments minimum distance estimator.

Trade Costs

To estimate trade costs, I draw on matched data on prices and the location of production of models for a subset of countries and use Equation (11), which represents the optimal price equation derived from the model.

I interpret differences in prices of specific car models that are produced in a single location, and are sold in different markets as being driven by trade costs τ_{ij}.[33] I cannot recover bilateral trade costs for each pair of markets since I do not have price data for all the markets. Instead, I parameterize τ_{ij} as:

$$\tau_{ij} = (1 + \text{tariff}_{ij})^{\phi_{tar}} d_{ij}^{\phi_{dist}} \tag{16}$$

where tariff_{ij} denotes tariffs between locations i and j for automobiles and d_{ij} denotes a measure of distance between locations i and j. The parameters ϕ_{tar} and ϕ_{dist} are identified by the following

[32] In Appendix B.2, I provide a discussion about the construction and processing of these variables.
[33] See e.g. Anderson and van Wincoop (2004), Atkin and Donaldson (2015) and Donaldson (2018).

linear regression:

$$\log(p_{ijm}) = \phi_{tar} \log(1 + \text{tariff}_{i(m),j}) + \phi_{dist} \log d_{i(m),j} + \alpha_{m,i(m)} + \alpha_j + u_{ijm}. \tag{17}$$

My dataset allows me to add a model-plant fixed effect, $\alpha_{m,i(m)}$, that controls for the unobserved marginal cost for model m in location i, subsuming the fundamental productivity of the firm, wages, firm-origin specific shocks, and the Lagrange multiplier associated to the capacity constraint. Through the inclusion of these fixed effects, I can control for unobserved production costs that could potentially bias the estimates. Since the prices in the dataset correspond to MSRPs and not final prices, I interpret the error term u_{ijm} as a measurement error.

Table 2: Estimation of Trade Costs

	(1) Log Price	(2) Log Price	(3) Log Price
Log Distance		0.033***	0.028***
		[0.002]	[0.003]
Log Tariff	1.061***	0.834***	1.000
	[0.066]	[0.075]	
Observations	2,590	2,590	2,590
R-squared	0.973	0.973	0.973
Model-Origin-Year FE	Yes	Yes	Yes
Market FE	Yes	Yes	Yes

Notes: This table shows OLS estimates for Regression Equation (17). The dependent variable is the log price for model m, produced in plant i, and sold in country j. The independent variables are log distance between plant i and market j and tariffs in market j and the country where plant i is located. All the specifications include model-plant fixed effects. In Column (3), I am fixing the coefficient on log tariffs to 1. Standard errors clustered at the plant level reported in brackets. Significance levels: ***$p < 0.01$, **$p < 0.05$, * $p < 0.1$.

Table 2 presents the results from estimating trade costs using Equation (17). My preferred specification is the one in Column (2), where I include a measure of geographic distance and of tariffs.[34]

Demand Elasticity, Home Market Effects, and Brand-Specific Quality

To estimate the elasticity of substitution, I leverage the fact that I observe prices and quantities for some countries and use the demand function described in Equation (5). Taking logs and adding a measurement error in prices, I get:

$$\log Q_{jn} = -\sigma \log p_{jn} + \log R_j + (\sigma - 1) \log P_j + \log \psi_{jn} + \sigma u_{ijn}. \tag{18}$$

[34]Notice that the coefficient on tariffs is different from one as it is usually presumed in the literature. This might be a reflection of imperfect pass-throughs due to the existence of variable markups, which I abstract from in the model to preserve computational feasibility.

I assume that the demand shifter ψ_{jn} is made up of two components. The first term is a firm-specific quality term γ_n that explains why, at the same prices, some brands have larger sales than others. The second component corresponds to a home bias term in demand that captures whether consumers in market j have stronger preferences for brands originated in that country, i.e., holding prices and qualities fixed there is a larger demand in Japan for Japanese cars than for German cars. Thus,

$$\log \psi_{jn} = \gamma_n + \delta^{H,D} BrandHome_{jn}. \tag{19}$$

Given that the data comes at the model level but the relevant elasticity of substitution from the perspective of the model is across varieties of different firms, I use a nested logit structure to collapse models of the same firm into quantity- and price-composites at the firm level. Specifically, first I estimate the following share regression at the model-market level,

$$\log \frac{p_{jmnt} q_{jmnt}}{\sum_{m \in N} p_{jmnt} q_{jmnt}} = (1 - \sigma_m) p_{jmnt} + P_{jnt} + v^m_{jmnt}. \tag{20}$$

where P_{jnt} is the ideal price-composite for firm n in market j in time t. Then, I used another share regression at the firm-market level to estimate the elasticity of substitution across firms including the demand shifter ψ_{jn},

$$\log \frac{P_{jnt} q_{jmnt}}{\sum_{m \in N} P_{jnt} q_{jmnt}} = (1 - \sigma_n) P_{jnt} + \rho_{nt} + \gamma_{bn} + \delta^{H,D} BrandHome_{jn} + v^n_{jnt}. \tag{21}$$

Table 3: Demand Elasticity, Brand Shifters and Home Market Effects

Strategy:		Nested		Single Nest
Nest:	Inner	Outer	Outer	
	(1)	(2)	(3)	(4)
	Log Share	Log Share	Log Q	Log Q
Log Price$_{jm}$	-3.280***			-3.887***
	[0.343]			[0.201]
Log Price$_{jn}$		-1.593***	-2.154***	
		[0.170]	[0.169]	
Home Market		1.068***	1.001***	0.636***
		[0.154]	[0.161]	[0.124]
Observations	4,810	617	617	4,885

Notes: This table shows estimates for Regression Equation (21). Columns (1) and (4) correspond to first stage regressions of log prices on log tariffs. Columns (2) and (5) correspond to OLS regressions of log quantities on log prices. Columns (3) and (6) show the IV estimates of regression of log quantities on log prices, instrumenting log prices by log tariffs. All the specifications contain market-year fixed effects. Specifications in columns (4) to (6) also contain fixed effects at the brand-level and a home market effect that is a dummy variable equal to 1 if the brand that produces model m is headquartered in market j. Standard errors clustered at the market-brand level reported in brackets. Significance levels: ***$p < 0.01$, **$p < 0.05$, * $p < 0.1$.

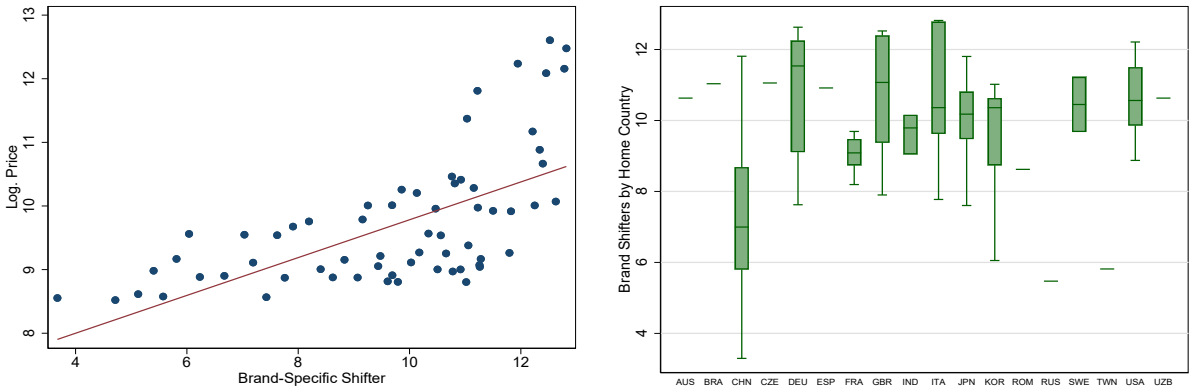
To estimate the elasticity of demand in Equation 20, I use tariffs as an instrument for prices.

An instrument is needed for two reasons. First, I assume that I observe prices with a measurement error, and then, estimation by OLS is affected by the usual attenuation bias. Second, there is potential for reverse causality. In this model, marginal costs are not constant, and therefore, prices are affected by the structural determinants of quantities.

In Table 3, I present the results from the regression in Equations (20) and (21). I show the instrumental variable estimation results from the inner nest in Columns (1) from Equation (21), and the results from estimation Equation (21). In Column (3), I show the estimates for the outer nest of an alternative regression that estimates the elasticity using the demand equation rather than the share equation. In Column (4), I show the results of estimating a demand equation that has a single nest, i.e that assumes that there is one elasticity of substitution across models within and across firms, where prices are instrumented by tariffs. The preferred specification is the one in Column (2), which includes brand fixed effects. I compute a demand elasticity of approximately across models of the same firm of 4.3 and across firms of 2.6 and a home market effect of around 1.0. This demand elasticity across models is quite similar to the one obtained in Head and Mayer (2019), who estimate an elasticity of 3.9, without leveraging price data. The home market effect is in line with Coşar et al. (2016) and is substantial.

In Figure 7, I present correlations of the brand shifters with prices, as well as the distribution of shifters by the home market of the firm. These brand shifters should be interpreted as measures of quality that explain why the demand for some brands is larger than for others after controlling for prices and home market effects. In Panel (a), I document that the estimated brand shifters have a strong positive correlation with prices. In Panel (b), I show the distribution of brand shifters by country of origin. It is easy to see that brands that originate in developing countries have smaller qualities.

Figure 7: Brand-Specific Demand Shifters



Notes: In Panel (a), I show a binscatter plot between log prices and the brand-specific qualities γ_n computed in the regression in Equation (21). In Panel (b), I show box plots with the distribution of brand qualities by the country of origin of each brand.

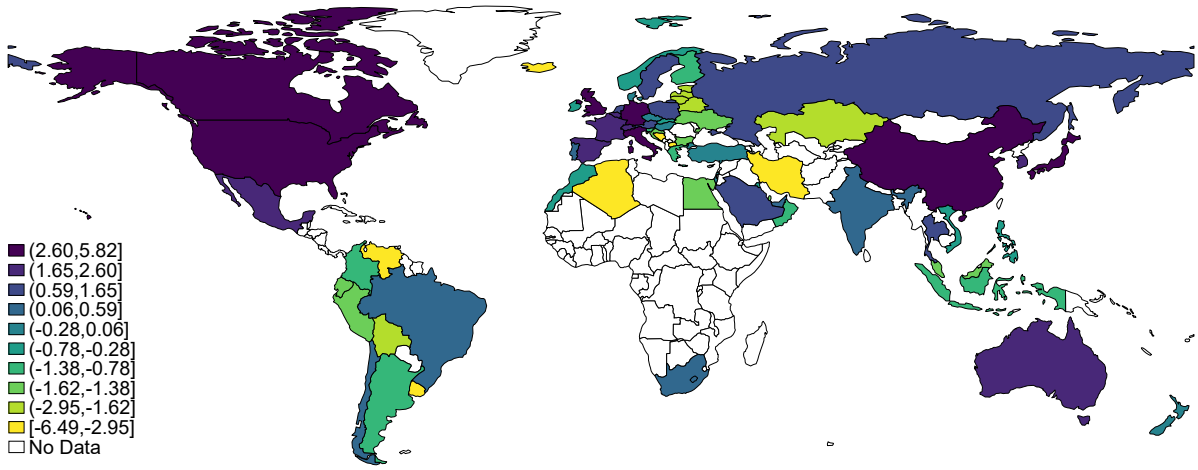
Market-Specific Shifters

To estimate the component of the firm-market shifters β_{jn} that is specific to market j, which I denote by δ_j and captures aggregate expenditure and the price index in that market, I also use the structural demand equation. However, I need to compute a different regression than in Equation (21), because I cannot retrieve shifters for all markets due to lack of data on prices. Instead, I substitute the optimal pricing equation and estimate:

$$\log Q_{i(m)jm} = \delta_1 \log(1 + \text{tariff}_{i(m)j}) + \delta_2 \log d_{i(m)j} + \delta_{i(m)m} + \delta_j + \delta^{H,D} BrandHome_{b(m)j} + \gamma_{b(m)} + \varepsilon_{i(m)jm}. \tag{22}$$

In Figure 8, I present the market-specific demand shifters δ_j in Equation (22). As expected, these shifters are the largest in markets with a large population and high income, like the United States.

Figure 8: Market-Specific Shifters



Notes: In this map, I plot the value of the market-specific fixed effects δ_j computed in the regression of Equation (22).

Distributions of Productivities and Investment Costs

To complete the estimation of the quantitative model, I need an estimation strategy for the vectors z_{in} and f_{in}. Unfortunately, I cannot use the structural equations implied by the model to recover these values using either a saturated regression or a model inversion. Therefore, I treat them as structural errors and assume that firms know them, but I, as a researcher, do not. I assume that these structural errors come from known parametric distributions, and I estimate the parameters that govern the distributions.

More precisely, I assume that the three distributions are Log-Normal. For both the firm-location specific shocks and the firm-location specific capacity costs, I assume that z_{in} and α_{in} are

drawn from the distributions $F^z_{in}(z_{in}) = \log\mathcal{N}(X'_{in}\delta^z + G'_i\delta^w, \xi^z)$ and $F^\alpha_{in}(\alpha_{in}) = \log\mathcal{N}(X'_{in}\delta^\alpha, \xi^\alpha)$, respectively. Conditional on the vector X_{in}, I assume that these draws are independent across firms and locations. Notice that I allow the mean of these Log-Normal distributions to vary across locations and firms. Specifically, I linearly project the mean on a vector of observable characteristics that attempt to proxy for fundamental determinants of how productive are on average plants and how costly it is to invest on capacity in a given location.[35] In contrast, I assume that for both distributions the dispersion parameters ξ^z and ξ^α are common across firms and locations.

I use a parsimonious set of observable characteristics contained in vector X_{in} to model the expectation of these distributions. I project these means on a constant, a set of geographic unit-specific variables that capture amenities and productivity, namely, measures of log gross domestic product per capita, log population, and log road density, a dummy variable equal to one when location i belongs to the country of origin of firm n to allow for home market effects in production, a measure of distance between location i and the firms' country of origin, and a measure of local land availability in location i to proxy for the price of land. I subsume the vector of wages in each location by adding the term $G'_i\delta^w$, where G_i are dummy variables that denote whether a particular location belongs to a country in one of six GDP bins, allowing productivity levels to flexibly vary across groups. Then, I use the structural model to estimate the parameters $\delta^z, \delta^w, \delta^\alpha, \xi^z$ and ξ^α.

I use the Simulated Method of Moments (SMM) to estimate the vector of parameters $\Theta = \{\delta^z, \delta^\alpha, \delta^w, \xi^z, \xi^\alpha, \kappa_1, \kappa_2\}$ following Gourieroux et al. (1993). To this end, I use the quantitative model described in Section 3, together with the vector of parameters that was estimated using the structural equations of the model as a data generating process with different simulation draws for the unobservable structural errors. The estimation procedure simulates a set of production and location choices for a set of artificial firms that behave according to the empirical model, a candidate parameter vector $\tilde{\Theta}$, and S vectors of simulations draws for the structural errors. These endogenous choices are translated into moments and averaged out across simulations. Then, the estimator finds the value of $\tilde{\Theta}$ for which the distance between m, the vector of moments in the data, and $\hat{m}(\tilde{\Theta})$, the simulated counterpart of these moments when the parameters are equal to $\tilde{\Theta}$, is minimized,

$$\hat{\Theta} = argmin_{\tilde{\Theta}} \left(m - \hat{m}\left(\tilde{\Theta}\right)\right)' W \left(m - \hat{m}\left(\tilde{\Theta}\right)\right). \tag{23}$$

The differences in these two vectors are weighted using a matrix W. I use a two-stage SMM estimator. In the first stage, I use a diagonal weighting matrix with entries inversely proportional to the square of the respective moment. Then, I use the optimal weighting matrix $W^{opt} = \hat{\Omega}^{-1}$, where Ω is the variance-covariance matrix of the moments.

Forty-eight empirical moments are chosen as targets for estimation.[36] Since I use more moments than parameters, the model is over-identified and variation in all the moments jointly determines all the parameters of the model. However, different sources of variation in these moments are more

[35] Another option would be to be fully flexible and estimate a mean by location, akin to a fixed effect. However this would create a high-dimensional problem that is computationally infeasible and that would likely produce noisy estimates given the granular level of the data.

[36] In Table F.1, I present the explicit equations for the estimation moments.

informative for some of the parameters and, therefore, will be associated with the identification of different parameters.

I use three blocks of moments. The first block is geared towards matching the current distribution of plants and car production across space. To do this, I define moments that interact the vector of observable characteristics X_{in} and income group dummies G_i with $\log Y_{in}$, log production in location i by firm n, and with D_{in}, a binary variable equal to 1 if firm n has a plant in location i.[37]

The second group of moments are included to match features of the distributions of total production, total number of plants, and plant production across firms. I include as moments the average of the logs of the number of plants and of total production, as well as the squares of those logarithms. Also, I incorporate moments that attempt to match various percentiles of the distributions of total production and total number of plants by firm. Moreover, I include the expectation of the cross product between the log of the total number of plants and the log of the total production to capture how these two variable covary. Finally, I include moments to match the average difference between the production of the largest plant and the second largest plant for firms with multiple plants and the average largest plant.

To estimate the parameters κ_1 and κ_2 that govern the decline in productivity after the occurrence of a flood, I simulate flood realizations within the model and I compare production in a plant with and without floods, holding the fundamentals and the capacity of the plant constant. I simulate disasters using the definition of 10-year and a 100-year floods, assuming that the former occur with a 10% probability and the latter have a 1% probability and match the model-implied responses to the long run averages estimated in Figure 2.

4.3 Results of the Structural Estimation

In Table 4, I show the results of the structural estimation. The standard errors are computed using the usual formula for simulated method of moments estimators provided in Gourieroux et al. (1993).[38]

Starting from the determinants of the capacity costs, α_{in}, the estimates suggest that in locations with a larger population, with higher road density, with large GDP per capita, and with more available land, the cost of a unit of capacity is, on average, smaller. Due to the expression for the expectation of the Log-Normal distribution, these estimates can be interpreted as elasticities. An increase of 1% in the population, road density, and GDP per capita of a location decrease the expected cost of capacity by 0.001%, 0.004% and 0.003%, respectively. The coefficient on land availability can be interpreted as a semi-elasticity; an increase in 1 percentage point in the share

[37] In Appendix F.1, I discuss the separate identification of the productivity and the investment cost parameters in the context of a simple example. Identification is achieved because of two reasons. First, the units of the marginal production costs and the capacity costs are different; the marginal costs are multiplied by wages and the capacity costs are not in labor terms. The second reason is that the marginal cost also include the firm fundamental productivity ϕ_n. As long as ϕ_n is different from 0, the response to a marginal change in the value of the productivity parameters affects the expected production cost different than a marginal change in the value of the capacity cost parameters.

[38] In Section F.3 of the Appendix, I discuss the fit of the model.

Table 4: Parameter Estimates of the Structural Model

Parameter	Description	Estimate
δ_0^α	Constant - Capacity Cost	1.539
δ_1^α	Log. Population - Capacity Cost	-0.001
δ_2^α	Log. Road Density - Capacity Cost	-0.004
δ_3^α	Log. GDP Per Capita - Capacity Cost	-0.003
δ_4^α	Home Dummy - Capacity Cost	-0.026
δ_5^α	Log. Distance HQ - Capacity Cost	0.046
δ_6^α	Land Availability - Capacity Cost	-1.000
ξ^α	Variance - Capacity Cost	0.000
δ_0^ε	Constant - Local Productivity	-4.389
δ_1^ε	Log. Population - Local Productivity	0.034
δ_2^ε	Log. Road Density - Local Productivity	0.018
δ_3^ε	Log. GDP Per Capita - Local Productivity	0.114
δ_4^ε	Home Dummy - Local Productivity	0.096
δ_5^ε	Log. Distance HQ - Local Productivity	-0.070
δ_6^ε	Land Availability - Local Productivity	-0.121
ξ^ε	Variance - Local Productivity	0.018
δ_2^w	Wage Shifter - Income Group 2	0.018
δ_3^w	Wage Shifter - Income Group 3	0.113
δ_4^w	Wage Shifter - Income Group 4	0.226
δ_5^w	Wage Shifter - Income Group 5	0.783
δ_6^w	Wage Shifter - Income Group 6	0.382
κ_1	Damage 100-Year Flood	0.244
κ_2	Damage 10-Year Flood	0.420

Notes: This table shows estimates for the parameters of the structural model introduced in Section 4.2. Estimated computed using SMM with the moments in Table F.1. Model fit is discussed in Appendix Section F.3. Standard errors computed using the formula for simulated method of moments estimators provided in Gourieroux et al. (1993).

of available land in a location decreases the expected cost in 1.0%. I find important home market effects in the cost of capacity. All else equal, the cost of a unit of capacity in the headquarters country of the firm is 2.6% smaller than in any other country. This home market effect is amplified by the fact that the costs of capacity increase, with an elasticity of 0.5%, as locations are farther away from the headquarters country of the firm.

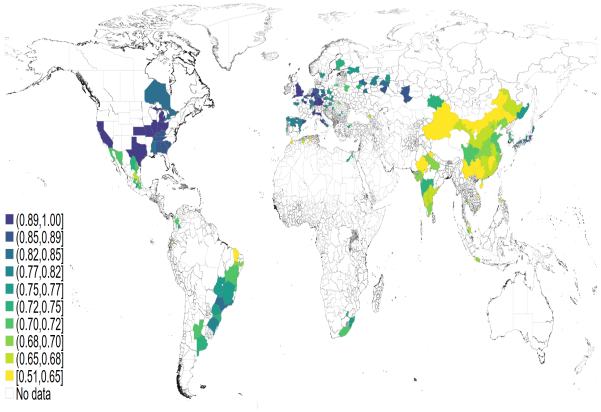
The average fundamental productivity of a location, z_{in}, increases by 0.034%, 0.018%, 0.114% and 0.121% with a 1% increase in population, road density and GDP per capita, and with a 1 p.p increase in land availability. Productivity is on average 10% larger for locations within the firms' home country and I find gravity in productivity; an increase in distance away from the home market reduces productivity with an elasticity of 0.07%.

I find sizable productivity penalties as a consequence of floods. To rationalize the impact of floods on car production estimated in Figure 2 through the lens of the model, the productivity after a 100-year flood decreases by approximately 90% and after a 10-year flood by 75%.

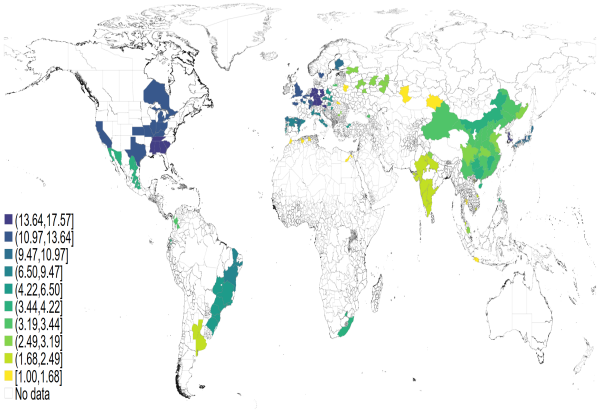
It is difficult to gauge the economic implications of the magnitude of these estimates from the numbers alone. In Figures 9 and 10, I explore the implications of these estimates for productivities, investment costs and the location of production.

Figure 9: Implications of Parameter Estimates

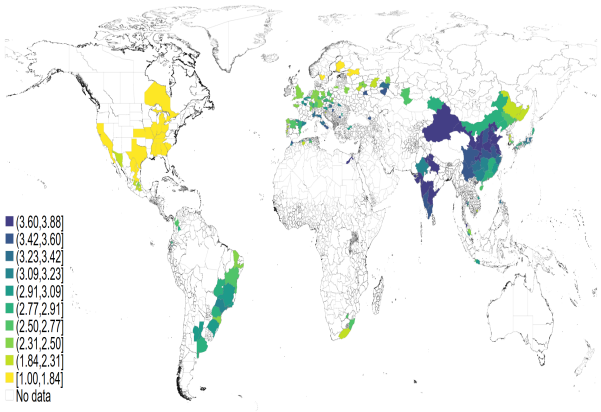
(a) Average Productivity - U.S Firms



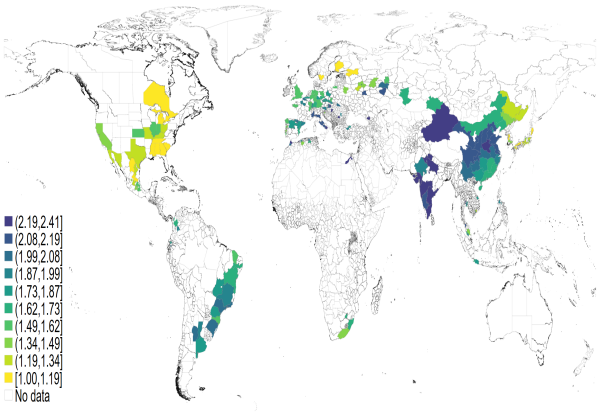
(b) Average Marginal Cost - U.S Firms



(c) Average Costs of Investing in Capacity - U.S Firms



(d) Average Costs of Investing in Capacity - Japanese Firms



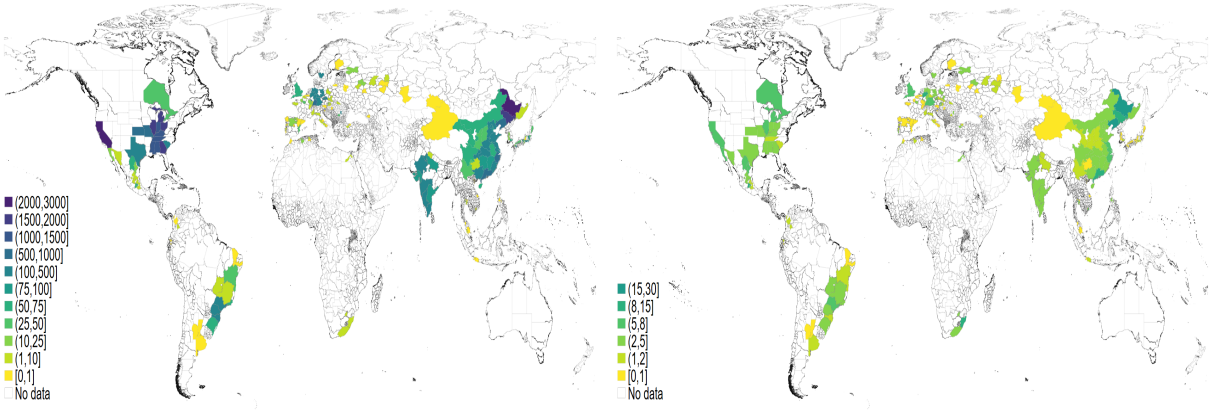
Notes: These maps show the values of average productivities and marginal costs for American firms, and average capacity costs for U.S and Japanese firms respectively. The values are normalized by the location with the largest productivity in Panel (a), and by the locations with the smallest value in the others.

In Figure 9a, I plot the average productivity for each GAUL1 administrative unit in the sample of U.S firms. I condition on firms from a particular origin as productivity is partly determined by the home country of each firm. The estimates reveal that the most productive locations are in the developed world, in places such as the United States, Canada, and Western Europe, reflecting the prominence of GDP per capita as a determinant of local car production productivity. However, what matters for production is how these productivity measurements interact with the costs of labor and the costs of capacity investment. In Figure 9b, I plot the average marginal cost of production in each location. Once one takes into account differences in wages across locations, the places with the smallest marginal costs are locations in developing nations such as India, China, and Mexico.

Figure 10: Model Implied Location of Production and of Plants

(a) Number of Produced Units

(b) Number of Plants



Notes: These maps show the number of cars (in thousands) and the number of plants generated by the model across 100 simulations. The locations taken into account correspond to the GAUL1 units where there is car production in 2019.

In Figure 9c and Figure 9d, I plot the average costs of investing in capacity for American and Japanese firms, respectively. As in the productivity case, the reason I analyze firms from a particular origin is that costs of capacity are, in part, determined by distance to the headquarter country of a firm. From these maps, it is clear that home market effects are important, as the cheapest country for investing for firms from both origins is the home country, whereas investing in China, for the U.S firms, or in South America, for the Japanese firms, seems very expensive highlighting the role played by distance to the origin country. The map shows that the other determinants related to local development matter as well. For instance, for U.S firms a unit of capacity is cheaper in parts of Europe than in Mexico. Likewise, for Japanese firms, a unit of capacity is cheaper in some locations in the United States than in China or India.

Figure 10 presents the geographical distribution of production and of plants as implied by the model. Ultimately, where firms decide to locate their plants and produce their goods is a function of three determinants. Due to the existence of trade costs, firms want to be close to large markets as measured by the firm-specific market shifter β_{jn}, at the same time that they produce in places that minimize the costs of producing goods given a level of capacity and the costs of building that capacity, and they want to have multiple firms to serve those markets in such a way that there production is resilient. The model predicts that plants locate mostly in North America, Central Europe, in particular in Germany and the Northeast of France, East India, South and North East China and Japan. The places in which the model predicts production strikingly resemble where production takes place in the data. In Figure B.1 in the Appendix, I show the number of plants and cars produced in the data for 2019.

5 The Effect of Changes in the Probability of Floods on Firm Organization

In this section, I evaluate how firm-level plant location, number, and capacity decisions respond to changes in the likelihood of extreme weather events occurring in different locations, how large are the costs of adaptation, and what are the implications of these responses for the location of consumption and production, average productivities, and consumer prices. The main counterfactual exercise involves modifying the probability distribution of extreme weather events and recomputing the extensive and intensive margin choices of the firms using the quantified structural model outlined in the previous sections. To do this, I combine the estimated values for the productivity declines caused by floods that rationalize the long run treatment effects computed in Section 2.3 with the parameter estimates of the structural model from Section 4.3 that match the distribution of car production in space, and with extreme precipitation event projected probabilities from a collection of different state-of-the-art climate models for three CO_2 emission scenarios which I describe in detail below.[39,40]

5.1 Projected Probabilities of Extreme Weather Events in the Future

To estimate the changes in probabilities of a weather disaster taking place in a specific region of the world, I draw upon climate projections from the Coupled Intercomparison Project Phase 6 (CMIP6) models. CMIP6 corresponds to the latest generation of CMIP, a standardized experimental framework for the systematic development, validation, and comparison of atmosphere-ocean general circulation models (Eyring et al. 2016). These projections are based on alternative future emission scenarios that attempt to capture possible pathways for societal development (O'Neill et al. 2016). The scenarios in CMIP6 are known as Shared Socioeconomic Pathways (SSPs).[41]

I define a flood disaster using as a proxy the occurrence of a five-day rainfall event that exceeds the historical threshold for a location-specific 10 year and 100 year return period. By construction, these events have occured with probability 10% and 1% in the historical data. Then, I measure

[39] I assume that the estimated damage caused by floods in production using historical data will be the same in the future. This is clearly a strong assumption as it is assuming away other endogenous potential adaptation mechanisms that might ameliorate the catastrophic impacts of extreme precipitations and runoffs such as plant fortification, and improvements in flood management by private and public agents. Hence, I interpret the results of this exercise as a worst case scenario in which firms can adapt just by changing their plant configuration.

[40] In these counterfactuals, I focus on extreme flooding events only, one particular weather disaster that is expected to be exacerbated in terms of severity and frequency by climate change. However, in this exercise I abstract from two relevant aspects. First, global warming will have persistent impacts on mean temperature and precipitation levels across space that will affect different locations heterogeneously. I abstract away from these changes in the averages, and focusing, on changes in the probability of extreme negative events. Second, there are many potential disasters that are expected to be affected by climate change that might covary negatively with floods, such as droughts and wildfires, or might compound with floods, such as storms and landslides, causing a more catastrophic event.

[41] As defined in O'Neill et al. (2016), there are five main Shared Socioeconomic Pathways correspond to SSP1-1.9, SSP1-2.6, SSP2-4.5, SSP3-7.0, and SSP5-8.5. In this paper, I focus on three of them, SSP1-1.9, SSP3-7.0 and SSP5-8.5. These scenarios are different in their assumptions about their evolution of population, urbanization and the global economy, and in their climate forcings in 2100 which correspond to the difference between incoming and outgoing radiation.

the probability of these events as the change in the probability of a historical 10-year and 100-year five-day precipitation event happening in a given location under a particular Shared Socioeconomic Pathway for the period 2035-2064. To reduce the uncertainty from climate models, I use projections from a multi-model ensemble, i.e., projections come from simulations made by different modeling groups in the world within the CMIP6 protocol, capturing differences in modeling choices and parameterizations. These probabilities are sourced from the Climate Change Knowledge Portal maintained by the World Bank.

Although I do not measure the probability of floods directly, the main drivers of floods are periods of extreme rainfall, thus, extreme five-day precipitation event are a good proxy for the occurrence of floods.[42] Extreme precipitation events correlate with riverine floods, flash floods and coastal floods.[43] However, I abstract from using information on the hydrology of river systems around the world, on the topography and soil characteristics of different locations, and human-made levees, dams and barriers.[44]

It is helpful to describe briefly the climate change scenarios used in this paper as defined by the IPCC (2021a).[45] SSP1-1.9 corresponds to the low end of future emission, leading to global warming between 1.0^{o}C and 1.8^{o}C by 2100. This optimistic scenario achieves the Paris Agreement goal. SSP3-7.0 corresponds to a medium to high range emissions scenario, with a 2.8^{o}C to 4.6^{o}C warming by 2100. Finally, SSP5-8.5 is the worst case scenario and represents the high-end of emissions and of warming, between 3.3^{o}C and 5.7^{o}C by 2100.

The probabilities of extreme events are very heterogeneous across SSPs and, more importantly, across space due to the differences in geography, topography, and position in the globe of distinct locations.[46] For instance, taking SSP5-8.5 as a benchmark, the probabilities of a 100-year five-day precipitation event are expected to increase in Tennessee to 2.2%, in Michigan to 2.3%, and in Tokyo to 1.4%, whereas the probability in Tangier, Morocco decreases to 0.8%. In SSP3-7.0, the probabilities of extreme events in these places are respectively 2.5%, 1.9%, 1.7% and 0.7%.

In Figure 11, I present the probabilities in each GAUL1 administrative unit for 10-year extreme precipitation events in Panel (a) and 100-year events in Panel (b). These probabilities are projected by a Multi-Model Ensemble of CMIP6 Models for the time period 2035-2064 centered in 2050. As the maps show, these probabilities are very heterogeneous around the world ranging from places like

[42] Even if computationally challenging, floods can be simulated and projected in the following way. First, one can download multi-model precipitation projections and runoff data for a particular SSP. Then, these precipitation and runoff projections can be used as an input in high resolution models of river networks such as CaMA-Flood v4.0 (Yamazaki et al. 2011). This has the limitation that these procedure is only informative about river flooding.

[43] See e.g. IPCC (2012), Hirabayashi et al. (2013), Donat et al. (2016), Breugem et al. (2020), Hirabayashi et al. (2021), IPCC (2021a), IPCC (2022) for discussions on the impact of extreme precipitation on floods.

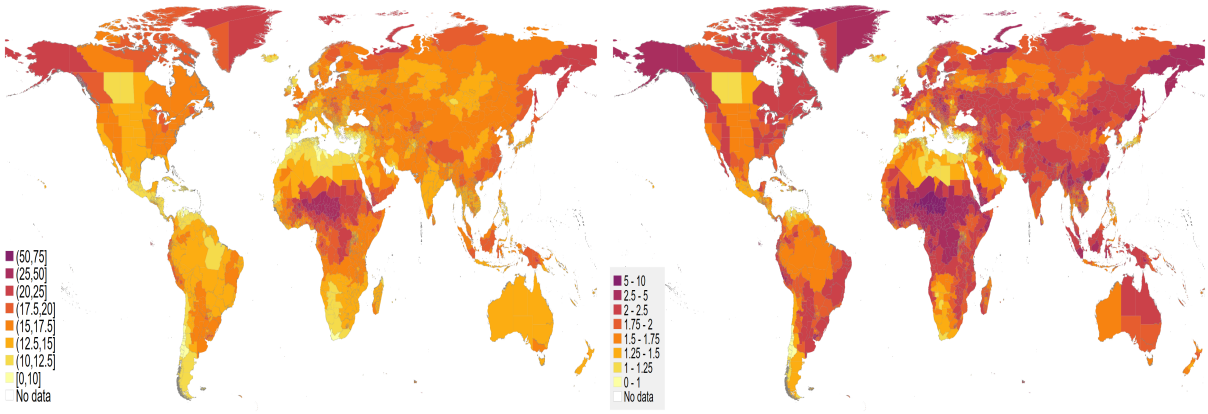
[44] For the United States, Bates et al. (2021) provide a composite assessment of floods hazard under future climate projections at a very high spatial resolution. This analysis takes into account pluvial, fluvial, and coastal flood hazards within the same framework taking into account realisitc topography, hydrology and current flood protections. There are companies such as Fathom that create global flood hazard maps using cutting edge hydrological models. Nonetheless, these come at a cost and do not have information about future climate projections.

[45] See Cross-Section Box TS.1: Global Surface Temperature Change in Arias et al. (2021).

[46] According to the IPCC (2021b), precipitation is projected to increase over high latitudes, the equatorial Pacific and parts of the monsoon regions. Moreover, ongoing global warming is projected to intensify the global water cycle, including its variability, global monsoon precipitation and the severity of precipitation events.

Figure 11: Extreme Precipitation Probabilities under SSP55-8.5

(a) 10-Year Event (b) 100-Year Event



Notes: These maps show the probability of historical 10-year precipitation events in Panel (a) and 100-year precipitation events in Panel (b). These projections come from a multimodel ensemble for SSP5-8.5 from the Climate Change Knowledge Portal of the World Bank. The administrative units in the map correspond to GAUL1 units.

North Africa, Turkey and the south of Spain, where extreme precipitation is predicted to become less likely to regions in Central Africa and Southeast Asia, where these probabilities are expected to increase by more than a factor of five.

The probabilities derived from the climatic models are processed by the Climate Change Knowledge Portal of the World Bank and provided at a $1^o \times 1^o$ global grid.[47] To arrive at a number at the GAUL1 level, I use the average of the gridpoints within the associated polygon of the shapefile.

5.2 Baseline Predictions

Table 5 documents how different assumptions on the distribution of climate change shocks affect the organization of production of firms. From this table, four patterns emerge. First, as the probability of adverse weather shocks to productivity increases, firms produce in more locations, but the capacity of these plants shrinks. That is, firms, on average, operate with a larger number of smaller plants. Comparing the current scenario, where 100-year floods happen with a 1% probability and 10-year floods with a 10% probability, and SSP5-8.5, the average firm increases its number of plants by 8.7%, but average capacity per plant decreases by 9.7%.

Second, firms shrink. For example, for the average firm, production capacity declines by 1.7% and profits by 3.8% between the current scenario and SSP5-8.5. In the counterfactual, the likelihood of an event that reduces productivity increases, and therefore, the expected productivity of each location is smaller. Hence, firms expected productivity declines, reducing their incentives to invest in size. Moreover, firms reallocate production capacity from ex-ante productive locations to places that are less productive, but give them the option to hedge. This implies a further decline in size

[47] See World Bank Group, Climate Change Knowledge Portal https://climateknowledgeportal.worldbank.org/.

as firms organize production in a more dispersed way across space, losing the productivity gains from concentrating production in the locations that produce at the lowest cost.

Third, firms operate with more spare capacity as shocks become more likely.[48] In a counterfactual world without shocks, firms operate at full capacity as there are no sources of uncertainty. As climate change becomes more severe and the likelihood of floods increases, firms start to hold more spare capacity to accommodate potential shocks to their other plants. This means that firms invest in resilience, even if most of the time, this spare capacity is not used. The benefit of being able to expand production in a plant if production in an affiliated plant is disrupted outweighs the cost of excess capacity if this additional capacity is idle or, even worse, if the plant itself suffers an adverse productivity event. In SSP5-8.5, firms reserve 13.5% of their total capacity for such hedging purposes.

Table 5: Firms' Plant Structure over Different Climate Change Scenarios

Extreme Precipitation Probability	**0%**	**1%/10%**	**SSP1-1.9**	**SSP3-7.0**	**SSP5-8.5**
Average Number of Plants	5.59	5.80	6.17	6.27	6.31
Average Capacity per Firm	362.64	349.94	347.47	346.97	343.70
Average Capacity per Plant	64.87	60.33	56.31	55.33	54.46
Average Profits	7130.82	6640.34	6472.67	6416.65	6387.53
Percentage Change	7.4%	0.0%	-2.5%	-3.4%	-3.8%
Average Investment	9684.24	9177.27	8949.25	8893.23	8859.01
% Negative Profits	0.00%	0.31%	0.44%	0.50%	0.46%
Average Used Capacity	100.0%	90.8%	87.7%	87.1%	86.5%
Average Capacity HHI	1.000	0.697	0.622	0.619	0.615
Average Production HHI	1.000	0.703	0.631	0.630	0.624

Notes: This table shows different statistics about the firms' plant organization over different climate scenarios. For each column, I am assuming firms make their capacity choices assuming different probabilities for extreme weather events, and that those events are generated according to those probabilities. In the first column, firms assume that extreme events do not happen. In the second column, 10-year events happen with a 10% probability and 100-year events happen with a 1% probability. This is the baseline scenario used to estimate the model. In columns 3 to 5, extreme weather event probabilities correspond to those in SSP1-1.9, SSP3-7.0 and SSP5-8.5, respectively. Statistics about capacity are in thousands of cars. Statistics about profits and investment are in millions of dollars. Average Used Capacity and Average Production HHI are computed in the realizations where there are no disasters.

Finally, both capacity and production become less spatially concentrated as measured by the Herfindahl-Hirschman Index. This follows directly from the fact that firms are spreading their plants and their production capacity in space.

In Table 6, I explore the extent to which the reconfiguration of the firms' production structure is effective as an adaptation mechanism to negative shocks. To do this, I compare profits when firms know that the probability of these shocks has changed and reallocate their plants accordingly, with profits in a case in which shocks occur according to the new probabilities, but firm choices are held fixed to the ones before climate change. I find that under different climate scenarios, adaptation in the spatial organization of production plants in response to a change in the probabilities of floods

[48] I compute this statistic by computing average spare capacity in cases where there are no realized shocks in the plants of the firm, in order to avoid the mechanical effect of floods reducing measured capacity utilization.

substantially reduces the decline in profits caused by climate change. For instance, the profits of the average firm decline by 3.8% between the current risk landscape and SSP5-8.5 when firms optimally adapt to the change in the probabilities. However, if there is a change in the probabilities of floods but firms do not adapt, the corresponding decline in profits is of 4.7%. That is, adaptation reduces the loss in profits due to climate change by around 20%. This finding is consistent across the different climate change scenarios.

Table 6: Effects of Adaptation on Profits

Extreme Precipitation Probability	**0%**	**1%/10%**	**SSP1-1.9**	**SSP3-7.0**	**SSP5-8.5**
Average Profits with Adaptation	7130.8	6640.3	6472.7	6416.7	6387.5
Relative to Scenario with 0%					
Decrease in Profits with Adaptation		-6.9%	-9.2%	-10.0%	-10.4%
Average Profits without Adaptation		6463.9	6223.6	6141.3	6078.5
Decrease in Profits without Adaptation		-9.4%	-12.7%	-13.9%	-14.8%
Losses from not adapting		-2.7%	-3.8%	-4.3%	-4.8%
Share of Losses Averted		26.5%	27.5%	27.8%	29.4%
Relative to 1%/10%					
Decrease in Profits with Adaptation			-2.5%	-3.4%	-3.8%
Average Profits without Adaptation			6451.4	6374.4	6330.4
Decrease in Profits without Adaptation			-2.8%	-4.0%	-4.7%
Losses from not adapting			-0.3%	-0.7%	-0.9%
Share of Losses Averted			11.2%	15.9%	18.4%

Notes: This table shows different statistics about firms' profits with and without adaptation over different climate scenarios. In the first row, I compute profits when firms adapt by choosing plant locations and capacities according to the probabilities for extreme weather events in the column. In the middle block, I compute when I hold fixed the capacity choices that are optimal when weather events happen with 0% probability, but the events are generated with the probability corresponding to the column. In the bottom block, I compute when I hold fixed the capacity choices that are optimal when weather events happen with 1%/10% probability, but the events are generated with the probability corresponding to the column.

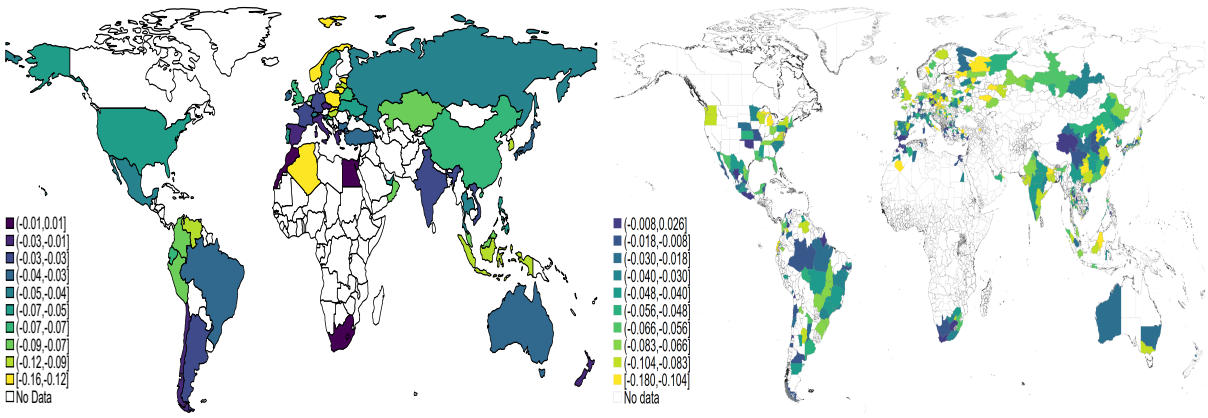
The implications for the spatial allocation of automobile production are shown in Figure 12a. The incidence of a future in which extreme weather events happen with a higher likelihood is very heterogeneous across countries. In most countries, production declines; however, there is a handful of countries, such as Morocco, Egypt, South Africa, Italy, and Spain, where total production increases or barely changes relative to the baseline. Actually, most of the reallocation of production takes place within countries. In Figure 12b, I compute the log change in production at the GAUL1 unit level. The map shows that production increases in regions in central Mexico, Northern Africa, the South of Spain, and the north of Italy. On the other hand, there is a decrease in production in England, the Northeast and the Great Lakes Regions of the United States, the eastern part of India, and the Northeast of France.

An important share of production relocates between different administrative units within the same country or trading bloc. Take the United States as an example. In Figure 12a, we see that production in the United States exhibits a considerable decline. Nonetheless, as Figure 12b shows,

Figure 12: Log Change in Production for SSP5-8.5

(a) Country Production

(b) GAUL1 Production



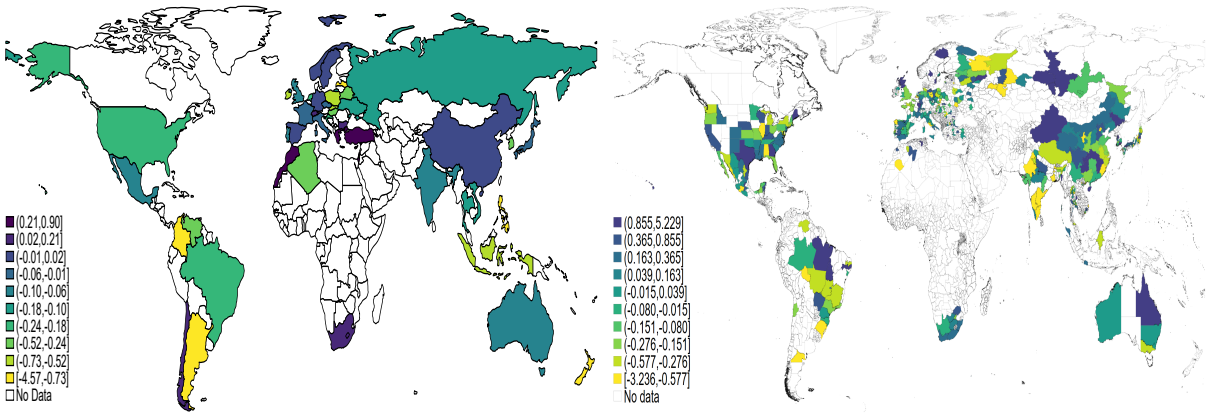
Notes: These maps show log changes in the number of cars produced between the current risk landscape, where 10-year floods occur with 10% probability and 100-year floods have a 1% probability, and the projected probabilities for SSP5-8.5, at the country-level in Panel (a) and at the GAUL1-level in Panel (b). The estimates used to simulate the model are in Table 4. The probability projections used come from a multimodel ensemble for SSP5-8.5 from the Climate Change Knowledge Portal of the World Bank. The administrative units in the map correspond to GAUL1 units.

this decline in production is mostly driven by changes in the location of production within the US; production is moving from very productive regions in the Northeast and the Great Lakes, for which extreme precipation probabilities are increasing considerably, to locations in the Great Plains that are less productive.

Figure 13: Log Change in Capacity for SSP5-8.5

(a) Country Capacity

(b) GAUL1 Capacity



Notes: These maps show log changes in capacity between the current risk landscape, where 10-year floods occur with 10% probability and 100-year floods have a 1% probability, and the projected probabilities for SSP5-8.5, at the country-level in Panel (a) and at the GAUL1-level in Panel (b). The estimates used to simulate the model are in Table 4. The probability projections used come from a multimodel ensemble for SSP5-8.5 from the Climate Change Knowledge Portal of the World Bank. The administrative units in the map correspond to GAUL1 units.

The impacts of climate change on production across space are mimicked by changes in total

capacity, as seen in Figure 13a. Firms shrink capacity in countries that become more affected by climate change and expand capacity in countries that are less affected. However, this adaptation mechanism interacts with market access in subtle ways. Firms do not substitute locations without taking into account how the new potential production sites impact their market access. Most of these substitutions take place between locations that are close to each other.

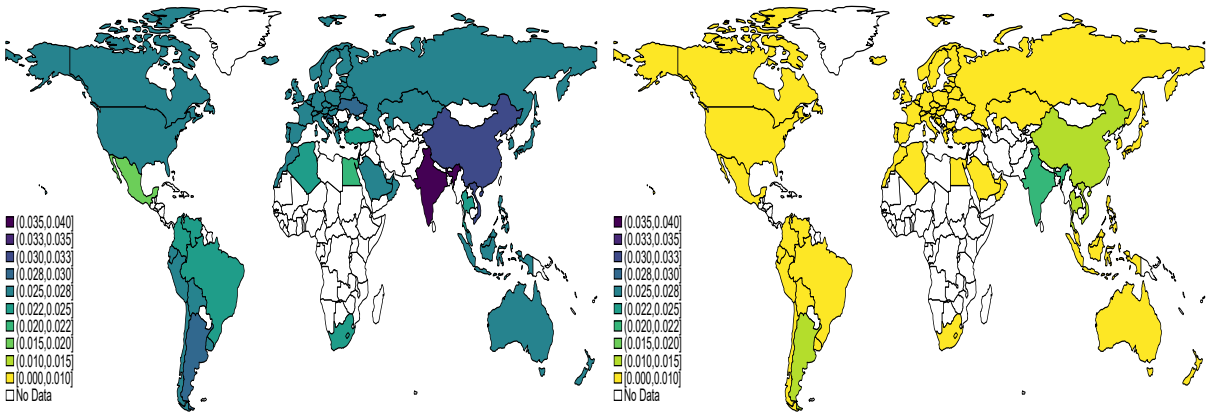
Figure 14a exhibits the impact of climate change on automobile price indices in each country in the sample. Following the model outlined in Section 3, increases in price indices are sufficient statistics for the negative effect that the increase in the probabilities of extreme events has on the utility that consumers derive from the automotive industry. In this map, I plot the log change in the price index in the baseline relative to the price index when extreme weather event probabilities are heightened by climate change. The industry price indices increase in almost all countries. The average price index rises by 2.6%. However, these increases are heterogeneous across space.

These price indices increase for three reasons. First, since the main counterfactual essentially constitutes a negative productivity shock becoming more likely, firms shrink in size. This reduces the number of cars that people can consume. Second, firms relocate their production sites from locations that are ex-ante optimal to places that are ex-ante suboptimal causing a decline in productivity. Third, the greater frequency of disasters exacerbates the decline in expected productivity, which in turn results in higher consumer prices.

Figure 14: Log Change in the Price Index for SSP5-8.5

(a) With Firm-Level Adaptation

(b) Without Firm-Level Adaptation



Notes: These maps show log changes in price indices defined by the formula in Equation (6) between the current risk landscape, where 10-year floods occur with 10% probability and 100-year floods have a 1% probability, and the projected probabilities for SSP5-8.5, when firms adapt to the new extreme precipitation probabilities in Panel (a) and when firms' choices are fixed to the ones in the baseline in Panel (b). The estimates used to simulate the model are in Table 4. The probability projections used come from a multimodel ensemble for SSP5-8.5 from the Climate Change Knowledge Portal of the World Bank. The administrative units in the map correspond to GAUL1 units.

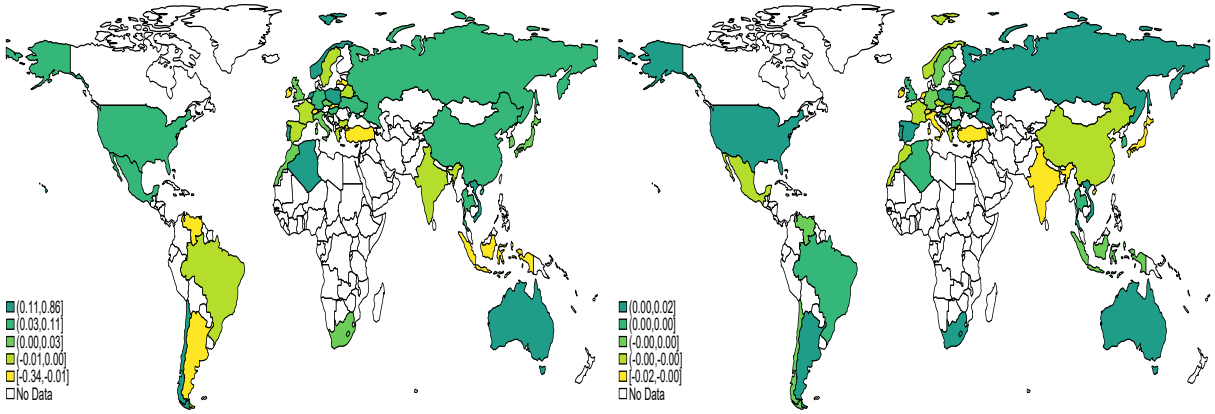
The fact that production is becoming more costly can be seen in Figure 15. In Panel (a), I show the average increase in marginal costs by country. In most countries, production costs increase. In fact, the average marginal cost, weighted by quantities produced, changes by 6.9%. Nonetheless,

in some countries the decrease in costs is mostly driven by the reallocation of productive firms to locations within those countries. In Panel (b), I show the change in average costs of capacity. On average, capacity costs declines by 0.03%. Although the effect is small, it reflects that when there is an increase in the probability of negative weather events, firms invest in capacity relatively more in places where capacity is less costly.

Figure 15: Log Change in Marginal Costs and Capacity Costs in SSP5-8.5

(a) Production Costs

(b) Capacity Costs



Notes: These maps show log changes in marginal production costs in Panel (a) and capacity costs in Panel (b) between the current risk landscape, where 10-year floods occur with 10% probability and 100-year floods have a 1% probability, and the projected probabilities for SSP5-8.5. In both cases, the country average is constructed as an average across the locations within the country weighted by the quantities produced in each location. The estimates used to simulate the model are in Table 4. The probability projections used come from a multimodel ensemble for SSP5-8.5 from the Climate Change Knowledge Portal of the World Bank. The administrative units in the map correspond to GAUL1 units.

In Figure 16, I decompose the increase in price indices into two components. The first component corresponds to the indirect productivity loss caused by the reallocation of production to ex-ante suboptimal locations and the reduction in capacity. The second term corresponds to the direct effect of weather disasters on productivity. I use the following decomposition,

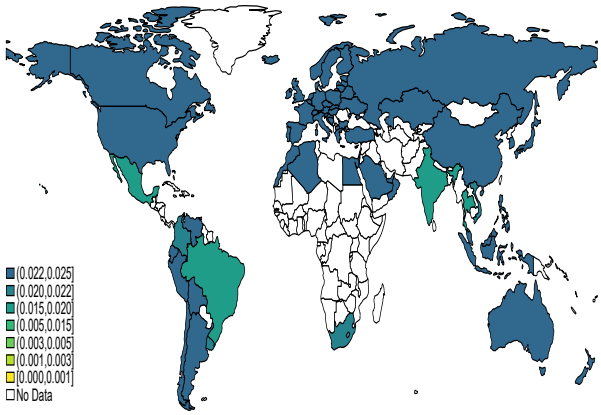
$$\frac{P_j^{'}}{P_j^o} = \frac{P_j^{',ns}}{P_j^o} \frac{P_j^{'}}{P_j^{',ns}},$$

where $P_j^{'}$ corresponds to the price index in country j after both the shocks become more likely and the plant configurations adapted as a result of the shock to the expectations, P_j^o is the value of the price index in country j at the baseline and $P_j^{',ns}$ is the ideal price index in country j when the firms' production organization has been adjusted in response to the change in probabilities, but the frequency of weather events are held at the baseline values. The first term corresponds to the effect of the change in the production structure and the second term to the effects of the shocks, conditional on the plant configuration. As seen in these figures, the main driver of the increase in price indices is the firm-level responses to climate change, rather than the direct impact of the weather shocks.

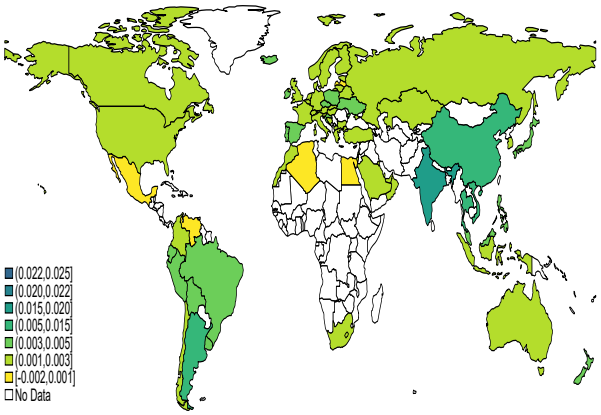
Finally, I evaluate the effect of firm adaptation on the welfare that consumers derive from

Figure 16: Decomposing the Effect in Consumer Prices
(Log Change)

(a) Indirect Effect of Reorganization



(b) Direct Effect of Weather Disasters



Notes: These maps show a decomposition of log changes in the price indices defined by the formula in Equation (6) between the current risk landscape, where 10-year floods occur with 10% probability and 100-year floods have a 1% probability, and the projected probabilities for SSP5-8.5, in an indirect effect coming from the spatial reorganization of production in Panel (a) and a direct effect of weather disruptions in Panel (b). The estimates used to simulate the model are in Table 4. The probability projections used come from a multimodel ensemble for SSP5-8.5 from the Climate Change Knowledge Portal of the World Bank. The administrative units in the map correspond to GAUL1 units.

the automotive industry. From comparing Figures 14a with 14b, it is clear that prices indices are higher, and the negative effect on consumer welfare is larger, when firms optimally respond to climate change than when they do not.[49] Thus, in this model, firm-level responses to climate change make consumers worse off. The reason for this is that, from the consumers' perspective, productivity shocks to individual firms are not very costly. There are many varieties and when the price of an individual variety increases due to an idiosyncratic disruption, consumers can substitute away to other products without generating a big impact on their welfare. This acts as a very efficient insurance mechanism for consumers. In contrast, firms have an inefficient technology to insure against weather shocks. Firms, on average, have a handful of plants, and creating new plants is costly. A disruption to one of these plants affects their surplus massively. When firms reallocate, aggregate productivity declines a lot as shown in Figure 16. From the perspective of the consumers, the relocation of plants across space is an aggregate shock. With firm-level adaptation, all varieties become, on average, more expensive due to the losses in productivity and capacity. This translates to an aggregate increase in automobile prices for consumers.

[49] In fact, a back-of-the-envelope calculation in which I convert these changes in the price indices to dollar values, suggest a decline of 2,067M in aggregate consumer surplus when firms adapt, but a 591M decline when firms do not adapt. Adding these numbers with the aggregate change in profits, these calculations suggest that total welfare declines by 38,174M when firms adapt, and by 46,800M when firms do not adapt.

6 Conclusion

An increase in the frequency and severity of disruptive weather events is an important consequence of climate change. This paper studies how firms adapt to a rise in the likelihood of floods by reorganizing their plant configuration through changes in their plants' location, number, and capacity. I explore these issues in the automotive industry, a global, large industry in terms of employment and value added, characterized by multinational and multiplant firms.

I document, using historical data, that severe floods have a significant impact on car production in plants near flooded areas. I show that firms offset part of the decline in production by ramping up the cars produced in other, similar plants within their production network. I develop a theoretical model in which multinational firms decide where to locate their production plants and how much capacity to install in each, conditional on the risk of extreme weather events. I estimate my model structurally to match the current geography of car production. Then, I combine the quantified model with projections from global climate models to simulate counterfactual scenarios where different probabilities of extreme weather events affect the distribution of production.

In the counterfactual analysis, I show that firms build additional plants in response to climate change, but these sites are smaller and operate with a larger spare capacity to accommodate adverse weather shocks in some of their plants. The increase in the probability of extreme weather events significantly affects profits, consumption, and welfare. However, adaptation through the reorganization of plants effectively reduces the impact of climate change on firms, cutting the loss in profits by a fifth. For consumers, firm-level adaptation reduces welfare. Consumers do not suffer much from supply disruptions when they have many varieties to choose from. By contrast, when firms reorganize their plants, there is an increase in the average price due to the losses in productivity and capacity. This provides a cautionary note for creating policies to incentivize resilience and manage disruption risks.

It is important to acknowledge two caveats. This paper focuses on a specific and well-defined margin of adaptation, which is the reorganization of production sites within the firm. In so doing, I assume away other margins of adaptation and potential changes in production and mitigation technologies. Also, I limit myself to one aspect of climate change and one particular weather disaster. However, global warming will have persistent impacts on mean temperature and precipitation levels across space, affecting different locations heterogeneously and potentially improving average productivity in some places. In addition, many potential weather disasters are expected to be affected by climate change, making some areas unattractive for reasons other than flood risk. This should be considered when interpreting the results on the reallocation of production across space.

Finally, the methodological tools developed in this paper can be adapted to study other sources of uncertainty, such as tariffs due to trade wars, trade costs due to potential transportation disruptions, wages due to labor strikes, or in demand shifters due to country-specific regulations or other aggregate shocks. Also, the optimization approach, could be convenient in alternative settings, such as in models of exporting or multinationals with increasing marginal costs and demand linkages, supply chain models, or optimal infrastructure models, among others.

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Appendix

A Cases of Weather Disruptions to Car Production

1. *Hurricane Ian forces Mercedes, Volvo to shutter S.C. plants after blasting Florida*, Automotive News, September 29, 2022
2. *Typhoon Hinnamoor halts production in Japan and South Korea*, Automotive Logistics, September 06, 2022
3. *Factory closures extended in China as drought continues*, Automotive Logistics, August 17, 2022
4. *Heavy rains hit Toyota production in Japan*, Automotive Logistics, August 02, 2022
5. *Floods hit auto production and supply in South Africa*, Automotive Logistics, May 30, 2022
6. *Drowned vehicles, stuck workers: Jeep, Ford plants halted amid Detroit flooding*, Detroit Free Press, June 30, 2021
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8. *GM to reopen Corvette plant after Ky. tornado*, Automotive News, December 17, 2021
9. *US tornado damage hits production and logistics*, Automotive Logistics, December 13, 2021
10. *Typhoon forces Subaru to halt production at Gunma*, Automotive Logistics, October 22, 2019
11. *Subaru halts production for 10 days after Typhoon Hagibis*, Nikkei Asia, October 17, 2019
12. *Auto industry still assessing impact of hurricane*, Automotive Logistics, September 19, 2018
13. *Mazda loses 44,000 units of output in Japan due to torrential rains*, Automotive News Europe, September 21, 2018
14. *Auto Industry anticipates production losses ahead of Hurricane Florence*, Freight Waves, September 12, 2018
15. *Japanese carmakers count the cost of natural disasters*, Automotive Logistics, September 11, 2018
16. *Toyota shuts South African plant after 'significant damage' from flooding*, Automotive Logistics, October 11, 2017
17. *Storm damage halts Toyota production in Durban*, Motorpress, October 10, 2017
18. *Hyundai and Kia Are Temporarily Closing Plants in Path of Irma*, The Drive, September 11, 2017
19. *OEMs and logistics providers assess damage from Hurricane Harvey*, The Drive, September 4, 2017
20. *FCA Minivan Production resumes as in Ontario as flood water recedes*, The Drive, August 29, 2017
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23. *Audi production in Germany hit by flooding*, Automotive News Europe, May 30, 2016
24. *Storm halts Toyota production in Texas*, Automotive Logistics, May 19, 2016
25. *Renewed flooding hits carmakers in India*, Automotive Logistics, December 2, 2015
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27. *Flooding in Chennai causes plant closures and supply disruption*, Automotive Logistics, November 18, 2015
28. *Detroit, Which Now Looks More Like Venice, Is So Flooded That Factories Have Been Affected*, Bangshift.com, August 13, 2014

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31. *Thailand floods stall automakers*, CNN Money, October 28, 2011

32. *Tornado Damage Closes Mercedes-Benz Alabama Plant*, Motortrend, April 28, 2011

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34. *Heatwave forces PSA Peugeot Citroen to trim output*, Automotive News, August 12, 2003

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36. *Flooding Forces PSA to Shut 5 Plants*, Automotive News, February 6, 1995

Figure A.1: The impact of flooding in Honda's Celaya plant

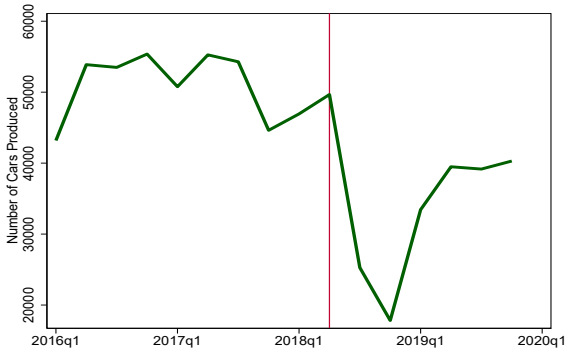
(a) Honda's Celaya Plant after Flood



(b) Location of Honda Plants in Mexico



(c) Production in Celaya Plant



(d) Production in El Salto Plant

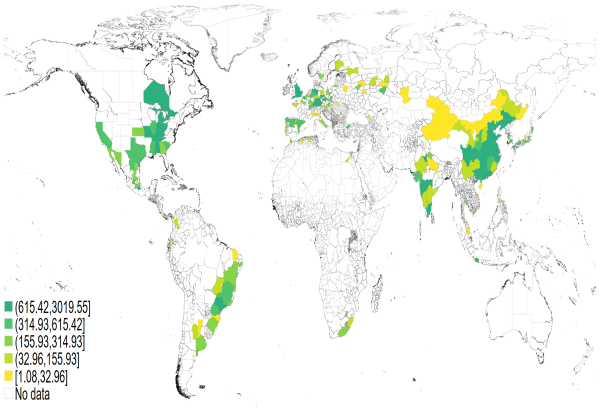


B Data Appendix

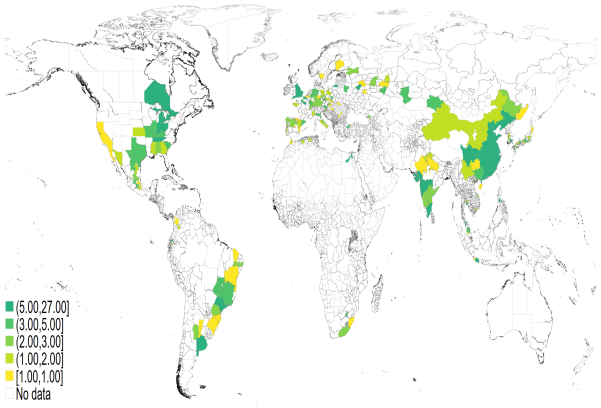
B.1 Global Car Data

Figure B.1: Data - Location of Production and of Plants

(a) Number of Produced Units

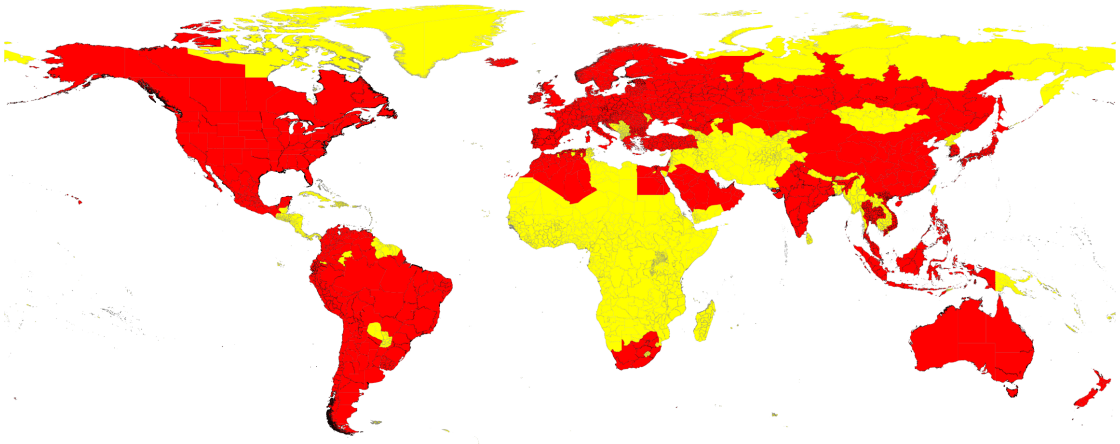


(b) Number of Plants



Notes: These maps show the number of cars (in thousands) and the number of plants in 2019. The locations taken into account correspond to the GAUL1 units where there is car production in 2019.

Figure B.2: Locations Included in the Counterfactuals



Notes: Regions in red are included in the counterfactuals of the model. These are regions in the countries with sales in the car registration dataset. The administrative units correspond to GAUL1 units.

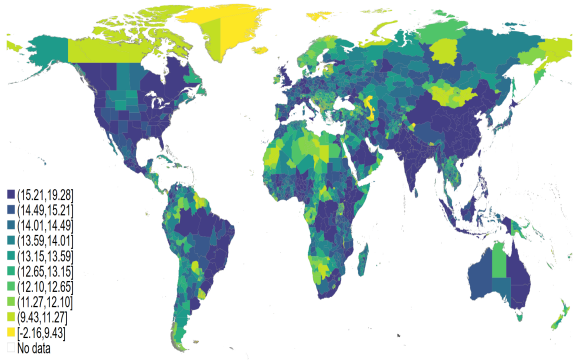
B.2 Location-Specific Variables

Local Population

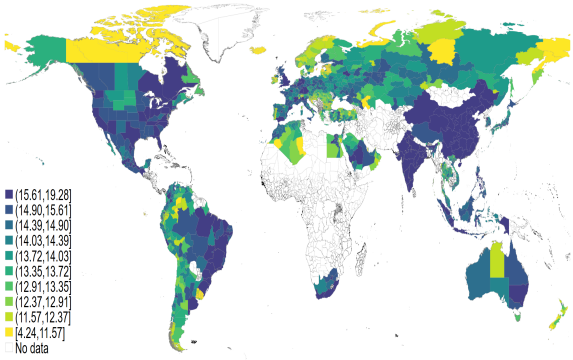
I source population counts in 2020 for each 1km grid from the WorldPop project (WorldPop 2021).[50] The high-resolution projections of the distribution of population around the world follow the methods presented in Lloyd et al. (2019). I convert the population counts for 1km grids to population counts at the GAUL1 level, by adding up the grids within the borders of each unit. For grids located in multiple GAUL1 units, population counts are apportioned proportionately.

Figure B.3: Local Population (in logs)

(a) All



(b) Locations in Counterfactual

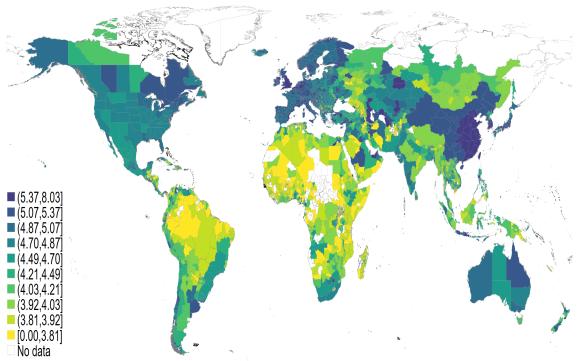


Local Road Density

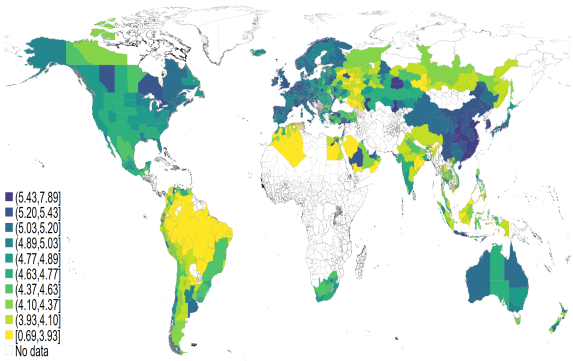
I construct measures of local road density using data from Meijer et al. (2018).[51] This dataset provides information of global and regional vector datasets in shapefile format, and global raster datasets of road density at a 5 arcminutes resolution. The dataset contains information for different types of roads. To construct my measure of road density, I compute the share of grids that contain primary roads or highways within a GAUL1 unit and compute the simple average.

Figure B.4: Local Road Density (in logs)

(a) All



(b) Locations in Counterfactual



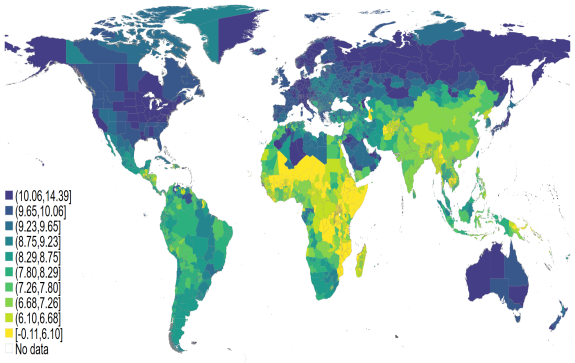
[50] This dataset can be downloaded in the following website https://hub.worldpop.org/geodata/listing?id=64.
[51] This dataset can be downloaded in the following website https://www.globio.info/download-grip-dataset.

Local Gross Domestic Product per Capita in PPP

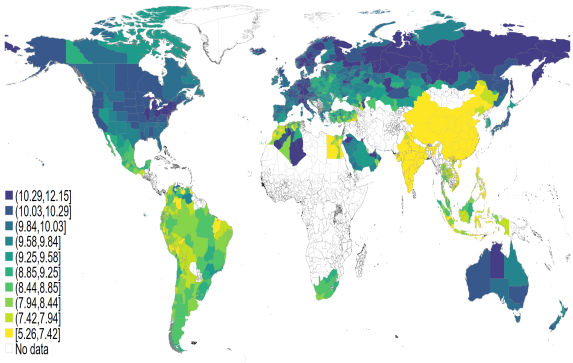
I construct measures of local gdp per capita using data from Kummu et al. (2018).[52] This dataset provides estimates of gross domestic product based on purchasing power parity at a 5 arc-min resolution for 2015. For each GAUL1 unit, I aggregate these estimates to get a value for gross domestic production at the GAUL1 level. Then, I divide by the GAUL1 population counts to get a measure of GDP per capita.

Figure B.5: Local Gross Domestic Product per Capita in PPP (in logs)

(a) All



(b) Locations in Counterfactual

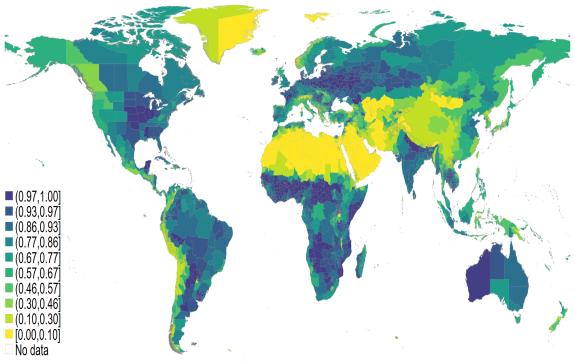


Local Land Availability

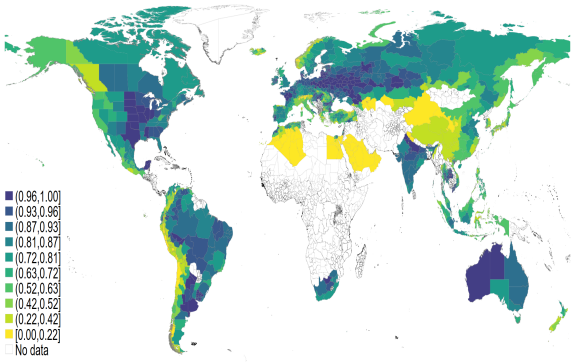
I define land availability in a given region as the share of undeveloped land, i.e., excluding buildings, croplands, marshes, glaciers, and deserts, with a slope smaller than 15%. I obtain information about global land use from the WorldCover project of the European Space Agency (Zanaga et al. 2021).[53] For each 10m by 10m pixel, I compute two variables. First, I compute its slope. Second, I compute whether the land is occupied by a building or a permanent crop, or by deserts, marshes or glaciers. For each GAUL1 unit, I compute the share of pixels that have buildable land.

Figure B.6: Local Land Availability (in Shares)

(a) All



(b) Locations in Counterfactual



[52]This dataset can be downloaded in the following website https://datadryad.org/stash/dataset/doi:10.5061/dryad.dk1j0.

[53]This dataset can be downloaded in the following website https://worldcover2020.esa.int/download.

C Additional Details of the Estimation Strategy

I estimate what is the causal effect of being affected by a flood on the car production of a plant. The treatment is coded as a binary variable in which a unit (a plant) is treated if in quarter q, plant i experiences a flood. Notice that under this definition, the treatment is not staggered, i.e., the value of the treatment for a particular unit might vary between 0 and 1 multiple times during the sample period. Also, the effects of these treatments are *potentially* heterogeneous across units and periods and dynamic, as being treated today might have repercussions on the future outcomes of a given unit. Therefore, the successful estimation of these causal effects begs for an estimator that yields consistent estimates under these conditions without imposing very strong assumptions. This is why I employ the estimator suggested in de Chaisemartin and D'Haultfoeuille (2022a). For completeness, I reproduce part of their analysis and their derivations below, trying to adapt and simplify their notation to my setting.

I assume the following statistical model for the effect of weather shocks on car production, as is conventional on applied literature,

$$Y_{it}(\boldsymbol{d}) = Y_{it}(\mathbf{0}_t) + \sum_{\ell=0}^{K} \gamma_{it}^{\ell} d_{t-\ell}. \tag{C.1}$$

This regression model imposes that only K treatment lags affect our outcome of interest and that these lags do not interact. Further assume that,

1. **No anticipation:** For all i, and for all possible sequence of treatments $\boldsymbol{d} \in \{0,1\}^T, Y_{it}(\boldsymbol{d}) = Y_{it}(d_1, \ldots, d_t)$. We can define the potential outcome at period t for observation i if it was never treated as $Y_{it}(\mathbf{0})$.
2. **Independent groups, strong exogeneity, and parallel trends for never-treated outcomes:** for all $t \geqslant 2$ and for all $i \in I$, $\mathbb{E}\left[Y_{it}(\mathbf{0}) - Y_{it-1}(\mathbf{0}) | \boldsymbol{D}\right]$ does not vary across units. For this assumption to hold, it is sufficient:
   (a) The vectors $(Y_{it}(\mathbf{0})_{1 \leqslant t \leqslant T}, \boldsymbol{D}_i)$ are mutually independent.
   (b) $\mathbb{E}\left(Y_{it}(\mathbf{0}) - Y_{it-1}(\mathbf{0}) | \boldsymbol{D}_i\right) = \mathbb{E}\left(Y_{it}(\mathbf{0}) - Y_{it-1}(\mathbf{0})\right)$
   (c) $\forall t \geqslant 2, \mathbb{E}\left(Y_{it}(\mathbf{0}) - Y_{it-1}(\mathbf{0})\right)$ does not vary across unit i.

Under these assumptions, it can be shown that estimating Equation C.1 by OLS using a regression of the outcome Y_{it} on unit and period fixed effects and dummy variables for the treatments $(D_{it-\ell})_{\ell} \in \{0, \ldots, K\}$ yields an estimate for the effect at ℓ, $\hat{\beta}_{\ell}$, periods after the treatment such that

$$\mathbb{E}\left(\hat{\beta}_{\ell}\right) = \mathbb{E}\left(\sum_{(i,t): D_{it-\ell} \neq 0, t \geqslant K+1} w_{it}^{\ell} \gamma_{it}^{\ell} + \sum_{\ell'=0, \ell' \neq \ell}^{K} \sum_{(i,t): D_{it-\ell'} \neq 0, t \geqslant K+1} w_{it}^{\ell} \gamma_{it}^{\ell'}\right) \tag{C.2}$$

where w_{it}^{ℓ} are weights proportional to the residuals in a regression of $D_{it-\ell}$ on $(D_{it-\ell'})_{\ell}' \in \{0, \ldots, K\}, \ell' \neq \ell$ and such that $\sum_{(i,t): D_{it-\ell} \neq 0, t \geqslant K+1} w_{it}^{\ell} = 1$ and $\sum_{(i,t): D_{it-\ell'} \neq 0, t \geqslant K+1} w_{it}^{\ell} = 0$ for every $\ell' \neq \ell$.

Therefore, the estimate that we retrieve from this canonical research design is a sum of $K+1$ terms. The first term corresponds to a weighted sum (with possibly negative weights) of the effect of the ℓth treatment lag on the outcome across its for which that treatment lag is equal to 1. This sum might be biased if there are heterogeneous effects across units and periods. The second group of sums are weighted sums of the effects on the outcome of other treatment lags. These effects might contaminate our estimate if these are heterogeneous as well. One thing that is noteworthy is that due to this second group of sums, even if there is no anticipation and with parallel trends, leads of a treatment can show up as being different from 0.

After recognizing these issues with the conventional regression strategy, de Chaisemartin and D'Haultfoeuille (2022a) develop an estimating strategy that attempts to circumvent these issues. First, they define the following parameters of interest

$$\delta_{i\ell} = \mathbb{E}\left(Y_{i,F_i+\ell}(\boldsymbol{D_i}) - Y_{i,F_i+\ell}(\mathbf{0}) | \boldsymbol{D}\right) \tag{C.3}$$

$$= \mathbb{E}\left(Y_{i,F_i+\ell}(\mathbf{0}_{F_i-1}, 1, D_{i,F_i+1}, \ldots, D_{i,F_i+\ell}) - Y_{i,F_i+\ell}(\mathbf{0}_{F_i+\ell})|\boldsymbol{D}\right) \tag{C.4}$$

where F_i is the first period at which i's treatment changes. In words, $\delta_{i\ell}$ is measuring the expected difference between unit i's actual outcome at period $F_i + \ell$, ℓ periods after it got treated for the first time and the counterfactual potential outcome in period $F_i + \ell$ if it had never been treated. We can aggregate these quantities to define

$$\delta_{+,\ell} = \sum_{i:F_i \leqslant T_u - \ell} \frac{\delta_{i\ell}}{N_\ell^1} \tag{C.5}$$

where $T_u = \max_i F_i - 1$ denotes the last period where there is still a group that has not been treated and $N_\ell^1 = \sum_{i:F_i < T_u - \ell} 1$, or the number of units, reaching ℓ periods after their first treatment at or before T_u. The quantity $\delta_{+,\ell}$ can be interpreted as the average effect on the outcome of interest of having switched treatment for the first time ℓ periods ago, across all groups that got treated for the first time at least ℓ periods before T_u.

Having defined these quantities, I need to define the estimators. To estimate $\delta_{i\ell}$, de Chaisemartin and D'Haultfoeuille (2022a) propose the following (conditionally) unbiased estimator

$$DID_{i\ell} = Y_{i,F_i+\ell} - Y_{i,F_i-1} - \sum_{i':F_{i'} > F_i+\ell} \frac{1}{\sum_{i:F_i > F_i+\ell} 1} \left(Y_{i',F_i+\ell} - Y_{i',F_i-1}\right) \tag{C.6}$$

which basically compares the evolution of the outcome for unit i between $F_i + \ell$ and $F_i - 1$ with the average evolution for units that are still untreated between the first period and $F_i + \ell$.

Then, they propose a conditionally unbiased estimator for $\delta_{+,\ell}$, which basically replaces $\delta_{i\ell}$ with their sample analogues,

$$DID_{+,\ell} = \sum_{i:F_i \leqslant T_u - \ell} \frac{DID_{i\ell}}{N_\ell^1} \tag{C.7}$$

The authors also derive placebo estimators that do not suffer from Rambachan and Roth (2019) critique and allow for testing of the parallel trends assumption. They define

$$DID_{i\ell}^p = Y_{i,F_i-\ell-2} - Y_{i,F_i-1} - \sum_{i':F_{i'} > F_i+\ell} \frac{1}{\sum_{i:F_i > F_i+\ell} 1} \left(Y_{i',F_i-\ell-2} - Y_{i',F_i-1}\right) \tag{C.8}$$

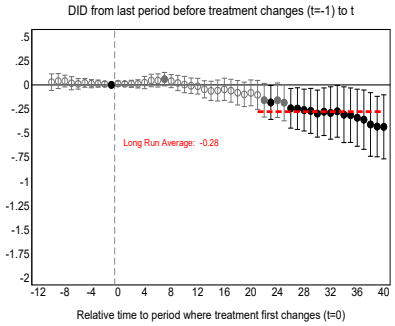
so that it compares the outcomes of i and other units not treated at $F_i + \ell$.

D Additional Reduced Form Exercises

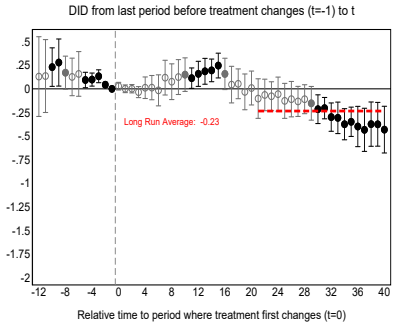
Figure D.1: The Impact of Severe Floods on Car Production - Other Outcomes

Number of Models

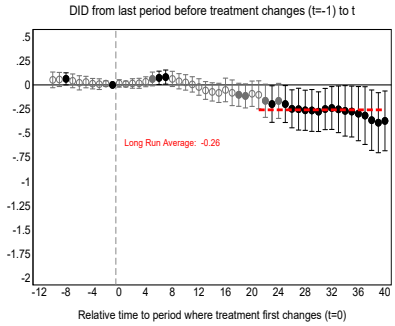
(a) All Floods



(b) 100-Year Floods

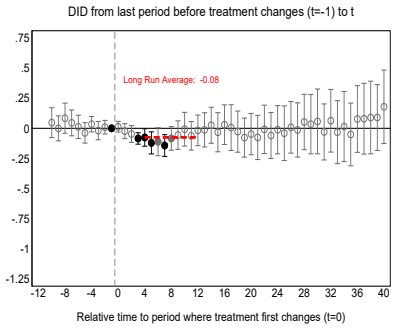


(c) 10-Year Floods

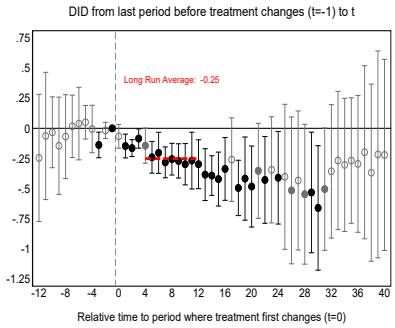


Average Production per Model

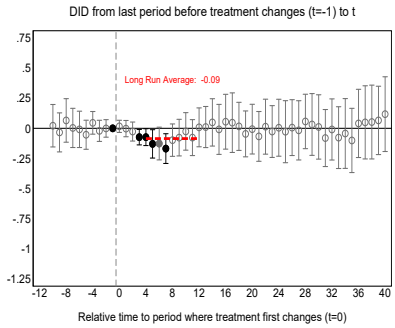
(d) All Floods



(e) 100-Year Floods

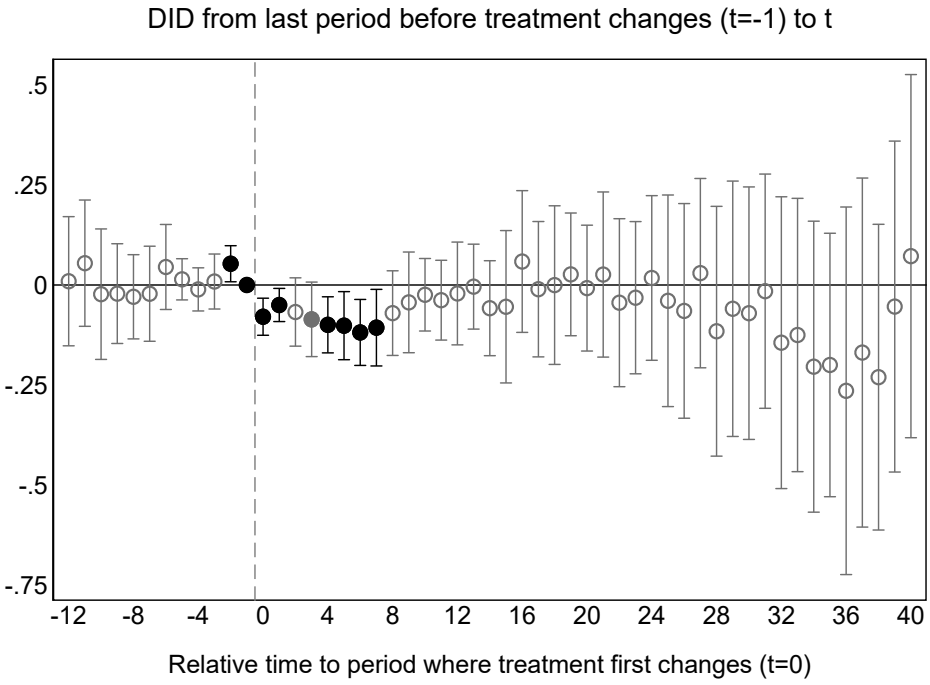


(f) 10-Year Floods



Notes: In these plots, the y-axis shows the values of Equation 2 for the outcome Log number of models produced in a plant in Panels (a) to (c) and log average production per model in Panels (d) and (f) for 0 to 40 quarters after the plant was flooded for the first time. The pre-trend estimates are computed using placebo estimators as described in Equation C.8. The sample comprises production plants that produce 50 units or more during all the quarters between 2000-2019 and did not experience any flooding events on the 20 quarters before the first period in the sample. Standard errors are clustered at the GAUL1 administrative level and computed with 100 bootstrap replications. The circles correspond to the point estimate, the bars correspond to 95% confidence intervals and the colors of the circle mean ● significant at 5%, ● at 10%, ○ not significant at 10%.

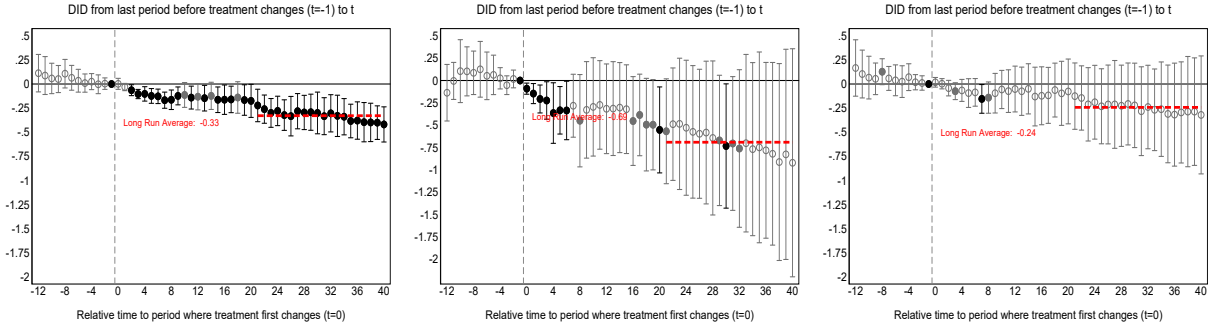
Figure D.2: The Impact of Severe Floods on Car Production - Total Firm Production



Notes: In these plots, the y-axis shows the values of Equation 2 for the outcome Log Total Production at the Firm-Level for 0 to 40 quarters after the firm experiences a flood in one of its plants for the first time. The pre-trend estimates are computed using placebo estimators as described in Equation C.8. The sample comprises production plants that produce 50 units or more during all the quarters between 2000-2019 and did not experience any flooding events on the 20 quarters before the first period in the sample. Standard errors are clustered at the GAUL1 administrative level and computed with 100 bootstrap replications. The circles correspond to the point estimate, the bars correspond to 95% confidence intervals and the colors of the circle mean ● significant at 5%, ● at 10%, ○ not significant at 10%.

Figure D.3: The Impact of Severe Floods on Car Production - Controlling for Spillovers

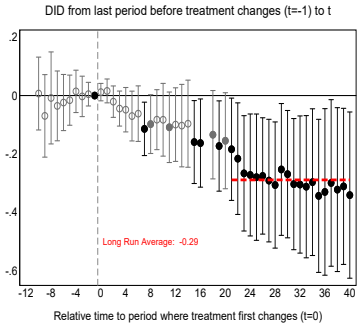
(a) All Floods (b) 100-year Floods (c) 10-year Floods



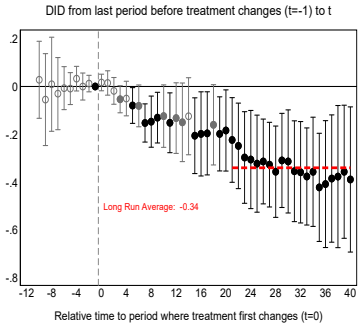
Notes: In these plots, the y-axis shows the values of Equation 2 for the outcome Log Plant Production for 0 to 40 quarters after the plant was flooded for the first time. I account for potential spillovers between plants of the same firm by using the modification proposed in Section 4 of de Chaisemartin and D'Haultfoeuille (2022b). The pre-trend estimates are computed using placebo estimators as described in Equation C.8. The sample comprises production plants that produce 50 units or more during all the quarters between 2000-2019 and did not experience any flooding events on the 20 quarters before the first period in the sample. Standard errors are clustered at the GAUL1 administrative level and computed with 100 bootstrap replications. The circles correspond to the point estimate, the bars correspond to 95% confidence intervals and the colors of the circle mean ● significant at 5%, ● at 10%, ○ not significant at 10%.

Figure D.4: The Impact of Severe Floods on Car Production - Alternative Thresholds

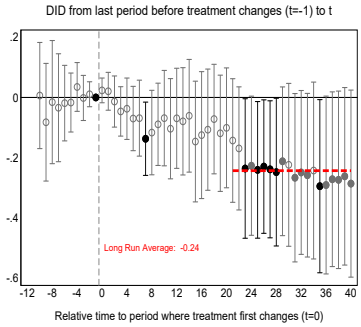
(a) 25 km



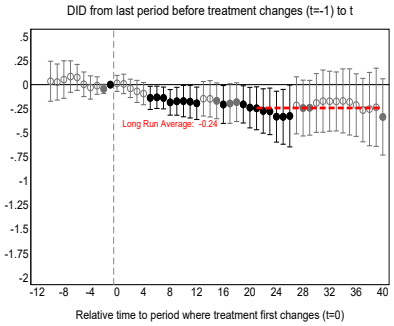
(b) 50 km



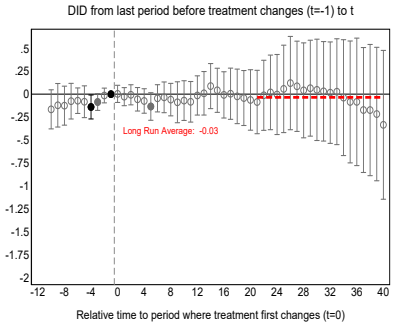
(c) 75 km



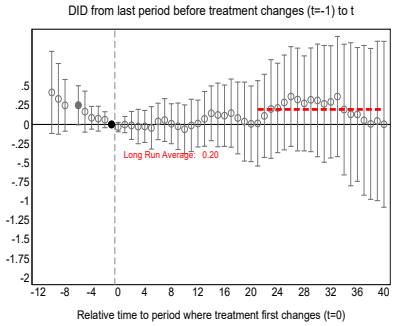
(d) 150 km



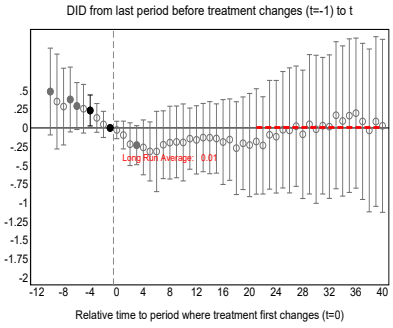
(e) 200 km



(f) 250 km

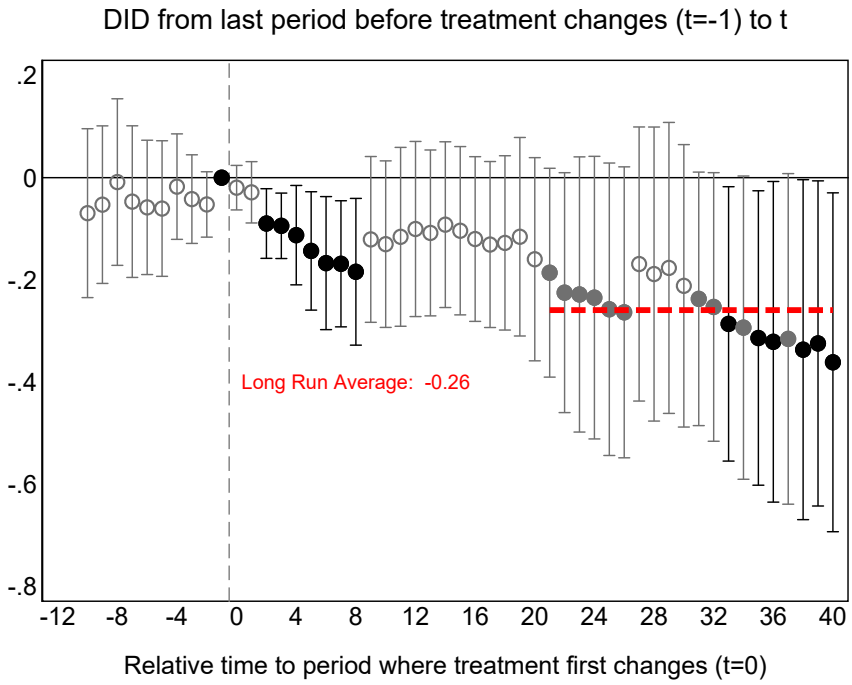


(g) 300 km



Notes: In these plots, the y-axis shows the values of Equation 2 for the outcome Log Plant Production for 0 to 40 quarters after the plant was flooded for the first time. The pre-trend estimates are computed using placebo estimators as described in Equation C.8. Floods are defined using different distance thresholds. The sample comprises production plants that produce 50 units or more during all the quarters between 2000-2019 and did not experience any flooding events on the 20 quarters before the first period in the sample. Standard errors are clustered at the GAUL1 administrative level and computed with 100 bootstrap replications. The circles correspond to the point estimate, the bars correspond to 95% confidence intervals and the colors of the circle mean ● significant at 5%, ● at 10%, ○ not significant at 10%.

Figure D.5: The Impact of Severe Floods on Car Production - Robustness to Country-Specific Fixed Effects



Notes: In these plots, the y-axis shows the values of Equation 2 for the outcome Log Plant Production for 0 to 40 quarters after the plant was flooded for the first time. In this estimator, I allow for production country-specific fixed effects. The pre-trend estimates are computed using placebo estimators as described in Equation C.8. The sample comprises production plants that produce 50 units or more during all the quarters between 2000-2019 and did not experience any flooding events on the 20 quarters before the first period in the sample. Standard errors are clustered at the GAUL1 administrative level and computed with 100 bootstrap replications. The circles correspond to the point estimate, the bars correspond to 95% confidence intervals and the colors of the circle mean ● significant at 5%, ● at 10%, ○ not significant at 10%.

E Proofs

Proposition 1 *The dual ex-post optimization problem of firm n conditional on a vector of capacities $\boldsymbol{C_n}$ and location productivities $\boldsymbol{\varepsilon_n}$ is*

$$\min_{\nu_{in}\geqslant 0} \sum_{i=1}^{I} \nu_{in} C_{in} + \frac{\left(\frac{\sigma-1}{\sigma}\right)^{\sigma-1}}{\sigma} \sum_{j=1}^{J} \beta_{jn}^{\sigma} \left(\min_{i} \left\{ \tau_{ij} \left(\frac{w_i}{\varepsilon_{in}} + \nu_{in} \right) \right\} \right)^{1-\sigma}$$

Proof *Start from the Lagrangian function of the Problem described in Equation 9,*

$$\mathcal{L} = \sum_{j=1}^{J} \beta_{jn} \left(\sum_{i=1}^{I} q_{ijn} \right)^{\frac{\sigma-1}{\sigma}} - \sum_{j=1}^{J} \sum_{i=1}^{I} \frac{\tau_{ij} w_i}{\varepsilon_{in}} q_{ijn} - \sum_{i=1}^{I} \nu_{in} \left(\sum_{j=1}^{J} \tau_{ij} q_{ijn} - C_{in} \right).$$

From the definition of the dual function,

$$D(\boldsymbol{\nu}_n) = \sum_{i=1}^{I} \nu_{in} C_{in} + \max_{q_{ijn}\geqslant 0} \sum_{j=1}^{J} \beta_{jn} \left(\sum_{i=1}^{I} q_{ijn} \right)^{\frac{\sigma-1}{\sigma}} - \sum_{j=1}^{J} \sum_{i=1}^{I} \tau_{ij} \left(\frac{w_i}{\varepsilon_{in}} + \nu_{in} \right) q_{ijn}.$$

The first order condition for an arbitrary q_{ijn} is given by

$$\frac{\sigma-1}{\sigma} \beta_{jn} \left(\sum_{i=1}^{I} q_{ijn} \right)^{-\frac{1}{\sigma}} - \tau_{ij} \left(\frac{w_i}{\varepsilon_{in}} + \nu_{in} \right) \leqslant 0.$$

Then, one can write the dual problem based on Wolfe (1961), as

$$\begin{aligned} \min_{\nu_{in}\geqslant 0} \quad & \sum_{i=1}^{I} \nu_{in} C_{in} + \frac{\left(\frac{\sigma-1}{\sigma}\right)^{\sigma-1}}{\sigma} \sum_{j=1}^{J} \beta_{jn} \left(\sum_{i=1}^{I} q_{ijn} \right)^{\frac{\sigma-1}{\sigma}} - \sum_{j=1}^{J} \sum_{i=1}^{I} \tau_{ij} \left(\frac{w_i}{\varepsilon_{in}} + \nu_{in} \right) q_{ijn} \\ s.t \quad & \frac{\sigma-1}{\sigma} \beta_{jn} \left(\sum_{i=1}^{I} q_{ijn} \right)^{-\frac{1}{\sigma}} - \tau_{ij} \left(\frac{w_i}{\varepsilon_{in}} + \nu_{in} \right) \leqslant 0 \quad \forall i,j \end{aligned}$$

This dual optimization problem can be further simplified by introducing the constraint in the objective function. From the first order condition, it must be the case that

$$Q_{jn} \equiv \left(\sum_{i=1}^{I} q_{ijn} \right) = \beta_{jn}^{\sigma} \left(\frac{\sigma-1}{\sigma} \right)^{\sigma} \left(\min_{i} \left\{ \tau_{ij} \left(\frac{w_i}{\varepsilon_{in}} + \nu_{in} \right) \right\} \right)^{-\sigma},$$

but also, implies that

$$\sum_{j=1}^{J} \sum_{i=1}^{I} \tau_{ij} \left(\frac{w_i}{\varepsilon_{in}} + \nu_{in} \right) q_{ijn} = \sum_{j=1}^{J} \sum_{i=1}^{I} \frac{\sigma-1}{\sigma} \beta_{jn} Q_{jn}^{-\frac{1}{\sigma}} q_{ijn} = \sum_{j=1}^{J} \frac{\sigma-1}{\sigma} \beta_{jn} Q_{jn}^{-\frac{1}{\sigma}} \underbrace{\sum_{i=1}^{I} q_{ijn}}_{Q_{jn}}$$

Then, replacing this in the dual function, the dual problem of the firm n is given by

$$\min_{\nu_{in}\geqslant 0} \sum_{i=1}^{I} \nu_{in} C_{in} + \frac{\left(\frac{\sigma-1}{\sigma}\right)^{\sigma-1}}{\sigma} \sum_{j=1}^{J} \beta_{jn}^{\sigma} \left(\min_{i} \left\{ \tau_{ij} \left(\frac{w_i}{\varepsilon_{in}} + \nu_{in} \right) \right\} \right)^{1-\sigma}.$$

Proposition 2 *The optimization problem described in Definition 1 can be written as the minimization of a linear objective function on a convex set.*

Proof *Starting from the problem in Definition 1, substitute the expression* $\min_i \left\{ \tau_{ij} \left(\frac{w_i}{\varepsilon_{in}} + \nu_{in} \right) \right\}$ *for a new variable* μ_j *for all* $j \in J$ *and add constraints for all* i *and all* j *such that* $\mu_j \leqslant \tau_{ij} \left(\frac{w_{in}}{\varepsilon_{in}} + \nu_{in} \right)$. *It becomes*

$$\min_{\nu_{in}\geqslant 0, \mu_{jn}>0} \sum_{i=1}^{I} \nu_{in} C_{in} + \frac{\left(\frac{\sigma-1}{\sigma}\right)^{\sigma-1}}{\sigma} \sum_{j=1}^{J} \beta_{jn}^{\sigma} {\mu_{jn}}^{1-\sigma}$$
$$s.t \;\; \mu_{jn} \leqslant \tau_{ij} \left(\frac{w_i}{\varepsilon_{in}} + \nu_{in} \right) \quad \forall i, j$$

To make the problem linear, notice that one can substitute $\mu_{jn}^{1-\sigma}$ *for* t_{jn} *and add power cones as constraints. A three-dimensional power cone is defined as*

$$P_3^{\alpha,1-\alpha} = \left\{ x \in \mathbb{R}^3 : x_1^{\alpha} x_2^{1-\alpha} \geqslant |x_3|, x_1, x_2 \geqslant 0 \right\}. \tag{E.1}$$

. The intuition is that I substitute the nonlinear term $\mu_{jn}^{1-\sigma}$ *for a new auxiliary variable* t_{jn} *such that* $t_{jn} \geqslant \mu_{jn}^{1-\sigma}$. *This nonlinear inequality condition can be formalized using a three-dimensional cone,* $(t_{jn}, \mu_{nj}, 1) \in P_3^{\frac{1}{\sigma},1-\frac{1}{\sigma}}$. *In the optimum, these two variables will coincide since minimizing the objective function involves choosing the smallest* t_{jn} *or the largest* μ_{jn} *possible. Then, the problem is*

$$\min_{\nu_{in}\geqslant 0, \mu_{jn}>0, t_{jn}>0} \sum_{i=1}^{I} \nu_{in} C_{in} + \frac{\left(\frac{\sigma-1}{\sigma}\right)^{\sigma-1}}{\sigma} \sum_{j=1}^{J} \beta_{jn}^{\sigma} t_{jn}$$
$$s.t \;\; \mu_{jn} \leqslant \tau_{ij} \left(\frac{w_i}{\varepsilon_{in}} + \nu_{in} \right) \quad \forall i, j$$
$$(t_{jn}, \mu_{nj}, 1) \in P_3^{\frac{1}{\sigma},1-\frac{1}{\sigma}} \quad \forall j$$

It is easy to see that the objective function is a linear function of ν_{in} *and* t_{jn}, *and that the first set of constraints are linear and, thus, convex. The power conic constraints are convex as well.*

Consider $(t_{jn}^o, \mu_{nj}^o, 1) \in P_3^{\frac{1}{\sigma},1-\frac{1}{\sigma}}$ *and* $(t'_{jn}, \mu'_{nj}, 1) \in P_3^{\frac{1}{\sigma},1-\frac{1}{\sigma}}$, *showing that the convexity of these sets amounts to showing that* $(\lambda t_{jn}^o + (1-\lambda) t'_{jn}, \lambda \mu_{jn}^o)^{1-\sigma} + ((1-\lambda)\mu'_{jn}, 1) \in P_3^{\frac{1}{\sigma},1-\frac{1}{\sigma}}$, *which is*

$$\begin{aligned} \lambda t_{jn}^o + (1-\lambda) t'_{jn} &\geqslant (\lambda \mu_{jn}^o)^{1-\sigma} + ((1-\lambda)\mu'_{jn})^{1-\sigma} \\ &\geqslant \left(\lambda \mu_{jn}^o + (1-\lambda)\mu'_{jn}\right)^{1-\sigma} \end{aligned}$$

where the first inequality follows from the definition of power cone and the second inequality from the fact that $f(x) = x^{1-\sigma}$ *is convex for* $x \geqslant 0$. ▫

Proposition 3 *The optimization problem described in Definition 14 is a concave objective function defined on a set of linear constraints.*

Proof *Since the capacity investment cost functions are convex and the constraints are conventional (linear) non-negativity constraints, it suffices to show that the expected operating profits function* $\mathbb{E}_{\boldsymbol{\varepsilon_n}}\left[\Pi_n(\boldsymbol{C_n}, \boldsymbol{\varepsilon_n})\right]$ *is concave in the vector* $\boldsymbol{C}$*. The expectation operator preserves the concavity of* $\Pi_n(\boldsymbol{C_n}, \boldsymbol{\varepsilon_n})$ *which is the only thing required to prove.*

Let $\boldsymbol{C}', \boldsymbol{C}'' \in \mathbb{R}_+^I$*, pick an arbitrary vector of productivities* $\boldsymbol{\varepsilon} \in \mathbb{R}_+^I$ *and* $\theta \in (0,1)$*. Define a function* $f(\boldsymbol{q}) = \sum_{j=1}^J \beta_{jn} \left(\sum_{i=1}^I q_{ij}\right)^{\frac{\sigma-1}{\sigma}} - \sum_{j=1}^J \sum_{i=1}^I \frac{\tau_{ij} w_i}{\varepsilon_{in}} q_{ij}$ *and a convex set* $D(\boldsymbol{C}) = \left\{q_{ij} : \sum_{j=1}^J \tau_{ij} q_{ij} \leqslant C_i,\ \forall i \in I, j \in J\right\}$*. Notice that the function* $f(q)$ *is concave. Let* $q' \equiv \operatorname{argmax}_{q \in D(C')} f(q)$ *and* $q'' \equiv \operatorname{argmax}_{q \in D(C'')} f(q)$*. Then,*

$$\begin{aligned}\Pi(\theta \boldsymbol{C}' + (1-\theta)\boldsymbol{C}'', \boldsymbol{\varepsilon}) \equiv & \max_{q \in D(\theta C' + (1-\theta) C'')} f(q) \geqslant \\ & f(\theta q' + (1-\theta) q'') \geqslant \\ & \theta f(q') + (1-\theta) f(q'') \\ = & \theta \Pi(\boldsymbol{C}', \boldsymbol{\varepsilon}) + (1-\theta)\Pi(\boldsymbol{C}'', \boldsymbol{\varepsilon}) \square\end{aligned}$$

Proposition 4 *An increase in the probability of floods in location* i*, decreases* C_i *in location* i *and weakly increases* C_j *in all other locations*

Proof *First, I am going to prove that for an arbitrary vector of capacities* $\boldsymbol{C}$*, and an arbitrary vector of productivities* $\boldsymbol{\varepsilon_{-i}}$*, which excludes the productivity in location* i*, if* $\varepsilon_i' < \varepsilon_i''$*, then* $\nu_i(\varepsilon_i'; \varepsilon_{-i}, \boldsymbol{C}) < \nu_i(\varepsilon_i''; \varepsilon_{-i}, \boldsymbol{C})$ *and* $\nu_{-i}(\varepsilon_i'; \varepsilon_{-i}, \boldsymbol{C}) \geqslant \nu_{-i}(\varepsilon_i''; \varepsilon_{-i}, \boldsymbol{C})$*. In words, the Lagrange multiplier in a given location is increasing in its own productivity and weakly decreasing in other locations productivities. Define the following function based on the reformulation of the dual problem in Equation 12:*

$$\min_{\nu_{in} \geqslant 0, \mu_{jn} > 0} \sum_{i=1}^I \nu_{in} C_{in} + \frac{\left(\frac{\sigma-1}{\sigma}\right)^{\sigma-1}}{\sigma} \sum_{j=1}^J \beta_{jn}^{\sigma} {\mu_{jn}}^{1-\sigma}$$
$$s.t\ \ \mu_{jn} \leqslant \tau_{ij}\left(\frac{w_i}{\varepsilon_{in}} + \nu_{in}\right) \quad \forall i, j$$

With KKT conditions given by,

1. $C_i - \sum_{j=1}^J \tau_{ij} q_{ij} + \lambda_i = 0$
2. $\frac{\left(\frac{\sigma-1}{\sigma}\right)^{\sigma-1}}{\sigma} \beta_{jn}^{\sigma} \mu_{jn}^{-\sigma} = \sum_{i=1}^I q_{ij}$
3. $\lambda_i \nu_i = 0$
4. $q_{ij}\left(\mu_{jn} - \tau_{ij}\nu_{in} - \tau_{ij}\frac{w_i}{\varepsilon_{in}}\right) = 0$

where q_{ij} *is the multiplier associated to the inequality constraints and* λ_i *is the multiplier associated to the nonnegativity constraints of* ν_i*. Moreover, as it is known from the reformulation,*

5. $\mu_{jn} = \min_i \left\{\tau_{ij}\left(\nu_{in} + \frac{w_i}{\varepsilon_{in}}\right)\right\}$

.

Without loss of generality, let's consider the case that ε_{in} *changes in a case in which the initial optimum* $\nu_{in} > 0$*. Since* ν_{in} *is positive, for some* j *it must be the case that* $\mu_j = \tau_{ij}\left(\nu_{in} + \frac{w_i}{\varepsilon_{in}}\right)$*. Now, if* ε_{in} *decreases, necessarily* μ_j *must increase.*

From condition 4, if location i *is still the least cost supplier of* j*, then since* μ_{jn} *is larger,* ν_{in} *must be smaller to restore the equality. Therefore,* ν_{in} *moves in the same direction as productivity. From standard optimal transport problem theory (see Galichon 2017), the* ν_{in} *can also be characterized as*

$$6.\ \nu_{in} = \max_j \left\{ \frac{\mu_{jn}}{\tau_{ij}} - \frac{w_i}{\varepsilon_{in}}, 0 \right\}$$

.

From this expression, we can derive the same result. Holding the value of the marginal market that is not served by i, but in which it would be profitable to do so, constant, a decline in ε_{in}, also reduces ν_{in}. The intuition is simple. Since the plant is becoming less productive, then the shadow value of capacity is smaller.

Now, take condition 6, for a plant different from i. Let me call this plant ℓ and reproduce the condition below,

$$6a.\ \nu_{\ell n} = \max_j \left\{ \frac{\mu_{jn}}{\tau_{\ell j}} - \frac{w_\ell}{\varepsilon_{\ell n}}, 0 \right\}$$

.

Now, assume that when productivity in i decreases, it must be the case that the cost of serving the different markets must weakly increase. In other words, the value of μ_{jn} must rise, for the markets for which i was the least cost supplier. Therefore, $\mu''_{jn} \geqslant \mu'_{jn}$ for all j. From condition 6a, this means that $\nu_{\ell n}$ weakly increases when ε_{in} decreases.

Once I have established that if $\varepsilon'_i < \varepsilon''_i$, then $\nu_{in}(\varepsilon'_i, \varepsilon_{-i}, \boldsymbol{C}) < \nu_{in}(\varepsilon''_i, \varepsilon_{-i}, \boldsymbol{C})$ and $\nu_{-in}(\varepsilon'_i, \varepsilon_{-i}, \boldsymbol{C}) > \nu_{-in}(\varepsilon''_i, \varepsilon_{-i}, \boldsymbol{C})$, then I need to show that investment in capacity in i necessarily decreases and that investment elsewhere weakly increases.

Now, let me start from the optimal vector of capacities $\boldsymbol{C}^{*\prime}$ before the disruption probabilities change. From the first order conditions, after the probability of the shock increase, in location i I am assigning more probability to a smaller value of ν_{in} and to large values of ν_{jn}, therefore, it must be the case that

$$\mathbb{E}\left[\nu_{in}(\boldsymbol{C}^{*\prime}, \boldsymbol{\varepsilon_n})\right] < \alpha_i$$
$$\mathbb{E}\left[\nu_{jn}(\boldsymbol{C}^{*\prime}, \boldsymbol{\varepsilon_n})\right] \geqslant \alpha_j, j \neq i.$$

To restore back to these equalities, capacity must decrease in location i, increasing the expected marginal return of capacity and must weakly increase elsewhere. This follows directly from the diminishing marginal returns of capacity. However, I provide a proof below.

Proposition 5 *Lagrange multipliers $\boldsymbol{\nu}$ are weakly decreasing in the vector of capacities $\boldsymbol{C}$, i.e take $C' \leqslant C''$, then $\nu(C'') \sqsubseteq \nu(C')$ (in the strong set order sense).*

Proof *Consider the negative of the dual function given by:*

$$h(\nu, C) = -\sum_{i=1}^{I} \nu_i C_i - \frac{\left(\frac{\sigma-1}{\sigma}\right)^{\sigma-1}}{\sigma} \sum_{j=1}^{J} \beta_j^\sigma \left(\min_i \left\{ \tau_{ij} \left(\frac{w_i}{\varepsilon_i} + \nu_i \right) \right\} \right)^{1-\sigma} \tag{E.2}$$

with $\boldsymbol{\nu}(\boldsymbol{C}) = \operatorname{argmax} h(\nu, C)$. To show that the maximizers of this function are decreasing in the parameter $\boldsymbol{C}$ *we can use the following theorem. If $h(\nu, C)$ has decreasing differences in (ν, C) and for every $\boldsymbol{C}$, $h(\cdot, C)$ is supermodular in $\mathbb{R}^N_+$, then $\boldsymbol{\nu}(\boldsymbol{C})$ is weakly decreasing in $\boldsymbol{C}$ in the strong set order sense.*

1. ***Decreasing differences:*** *Let $\nu' \leqslant \nu''$ and $C' \leqslant C''$, and consider*

$$h(\nu', C'') + h(\nu'', C') \geqslant h(\nu'', C'') + h(\nu', C')$$
$$-\sum_{i=1}^{I} \nu'_i C''_i - \sum_{i=1}^{I} \nu''_i C'_i \geqslant -\sum_{i=1}^{I} \nu''_i C''_i - \sum_{i=1}^{I} \nu'_i C'_i$$
$$\sum_{i=1}^{I} (C''_i - C'_i)(\nu''_i - \nu'_i) \geqslant 0$$

which holds by assumption. Notice that we can cancel the second term of the function, because it does not interact with the C.

2. ***Supermodularity:*** *Fix a value of $\boldsymbol{C}$. To show that $h(\cdot, C)$ is supermodular, we are going to first note that this function is a sum of two components. The first one is clearly supermodular as it is a linear function.*

   For the second term, define $g(\nu) = -\frac{\left(\frac{\sigma-1}{\sigma}\right)^{\sigma-1}}{\sigma} \sum_{j=1}^{J} \beta_j^{\sigma} \left(\min_i \left\{\tau_{ij}\left(\frac{w_i}{\varepsilon_i} + \nu_i\right)\right\}\right)^{1-\sigma}$, then we need to show that given $\nu', \nu'' \in \mathbb{R}_+^N$

$$g(\nu') + g(\nu'') \leqslant g(\nu' \vee \nu'') + g(\nu' \wedge \nu'') \tag{E.3}$$

   which means

$$\begin{aligned}
&-\sum_{j=1}^{J} \beta_j^{\sigma} \left[\left(\min_i \left\{\tau_{ij}\left(\frac{w_i}{\varepsilon_i} + \nu_i'\right)\right\}\right)^{1-\sigma} + \left(\min_i \left\{\tau_{ij}\left(\frac{w_i}{\varepsilon_i} + \nu_i''\right)\right\}\right)^{1-\sigma}\right] \leqslant \\
&-\sum_{j=1}^{J} \beta_j^{\sigma} \left[\left(\min_i \left\{\tau_{ij}\left(\frac{w_i}{\varepsilon_i} + \min\left\{\nu_i', \nu_i''\right\}\right)\right\}\right)^{1-\sigma} + \left(\min_i \left\{\tau_{ij}\left(\frac{w_i}{\varepsilon_i} + \max\left\{\nu_i', \nu_i''\right\}\right)\right\}\right)^{1-\sigma}\right] \Longrightarrow \\
&\sum_{j=1}^{J} \beta_j^{\sigma} \left[\left(\min_i \left\{\tau_{ij}\left(\frac{w_i}{\varepsilon_i} + \min\left\{\nu_i', \nu_i''\right\}\right)\right\}\right)^{1-\sigma} + \left(\min_i \left\{\tau_{ij}\left(\frac{w_i}{\varepsilon_i} + \max\left\{\nu_i', \nu_i''\right\}\right)\right\}\right)^{1-\sigma}\right] \leqslant \\
&\sum_{j=1}^{J} \beta_j^{\sigma} \left[\left(\min_i \left\{\tau_{ij}\left(\frac{w_i}{\varepsilon_i} + \nu_i'\right)\right\}\right)^{1-\sigma} + \left(\min_i \left\{\tau_{ij}\left(\frac{w_i}{\varepsilon_i} + \nu_i''\right)\right\}\right)^{1-\sigma}\right]
\end{aligned}$$

   a sufficient condition for this to hold is to show that it holds for an arbitrary j,

$$\begin{aligned}
&\left(\min_i \left\{\tau_{ij}\left(\frac{w_i}{\varepsilon_i} + \min\left\{\nu_i', \nu_i''\right\}\right)\right\}\right)^{1-\sigma} + \left(\min_i \left\{\tau_{ij}\left(\frac{w_i}{\varepsilon_i} + \max\left\{\nu_i', \nu_i''\right\}\right)\right\}\right)^{1-\sigma} \\
&\leqslant \left(\min_i \left\{\tau_{ij}\left(\frac{w_i}{\varepsilon_i} + \nu_i'\right)\right\}\right)^{1-\sigma} + \left(\min_i \left\{\tau_{ij}\left(\frac{w_i}{\varepsilon_i} + \nu_i''\right)\right\}\right)^{1-\sigma}
\end{aligned}$$

   which essentially means that we need to show that the function $f(x) = \min_i \{x_i\}^{1-\sigma}$ is submodular. To do this, notice first that $\min_i \{x_i\}^{1-\sigma} = \max_i \left\{x_i^{1-\sigma}\right\}$. Second, that

$$\begin{aligned}
\max_i \left\{x_i^{1-\sigma}\right\} + \max_i \left\{y_i^{1-\sigma}\right\} &\geqslant \max_i \left\{\max\{x_i, y_i\}^{1-\sigma}\right\} + \max_i \left\{\min\{x_i, y_i\}^{1-\sigma}\right\} \\
\max_i \left\{x_i^{1-\sigma}\right\} - \max_i \left\{\max\{x_i, y_i\}^{1-\sigma}\right\} &\geqslant \max_i \left\{\min\{x_i, y_i\}^{1-\sigma}\right\} - \max_i \left\{y_i^{1-\sigma}\right\} \\
\max\left\{0, \max_i \left\{x_i^{1-\sigma}\right\} - \max_i \left\{\min\left\{x_i^{1-\sigma}, y_i^{1-\sigma}\right\}\right\}\right\} &\geqslant \max\left\{0, \max_i \left\{x_i^{1-\sigma}\right\} - \max_i \left\{y_i^{1-\sigma}\right\}\right\}
\end{aligned}$$

   Thus $f(x)$ is submodular, and our original function is supermodular.

   Again, since a sum of supermodular function is supermodular itself, the $h(\cdot, C)$ is a supermodular function.

Finally, since both conditions hold, then the maximizers are decreasing in $\boldsymbol{C}$.

F Estimation

F.1 Separate Identification of Productivity and Capacity Costs

To convey the intuition behind the separate identification of the parameters that govern the distributions of z_{in} and α_{in}, let me consider a simplified example in which there is no uncertainty. Both z_{in} and α_{in} are known by the firm at the time of capacity choice. Since there is no uncertainty, the first order condition is

$$\nu_{in} \leqslant \alpha_{in} \ (= \Longleftrightarrow \ C_i > 0).$$

In terms of the marginal production cost perceived by the firm,

$$\frac{w_i}{\phi z_{in}} + \nu_{in} \leqslant \frac{w_i}{\phi z_{in}} + \alpha_{in} \ (= \Longleftrightarrow \ C_i > 0)$$

Based on this expression, I can compute the mean and variance of the marginal cost conditional on w_i, X_{in} and ϕ for locations in which the firms sets up plants.

$$\begin{aligned}
\mathbb{E}\left[\frac{w_i}{\phi z_{in}} + \alpha_{in}\right] &= \frac{w_i}{\phi}\mathbb{E}\left[\frac{1}{z_{in}}\right] + \mathbb{E}\left[\alpha_{in}\right] = \frac{w_i}{\phi} e^{-X'_{in}\delta^z} + e^{X'_{in}\delta^\alpha}, \\
\mathbb{V}\left[\frac{w_i}{\phi z_{in}} + \alpha_{in}\right] &= \frac{w_i^2}{\phi^2}\left[e^{\xi^z} - 1\right]\left(e^{-2X'_{in}\delta^z + 2\xi^z}\right) + \left[e^{\xi^\alpha} - 1\right] e^{X'_{in}\delta^\alpha}.
\end{aligned}$$

It is easy to see that the derivative with respect to δ^z is different from the derivative from the derivative with respect to δ^α for both the expectation and the variance. This is due to two reasons. The first reason is due to the units. Marginal costs are in terms of labor, and therefore, multiplied by wages, whereas capacity costs are in terms of a numeraire. The second reason comes from the functional form, and the fact that firm-specific productivity multiplies z_i. Thus, the effect of a change in δ_z on the mean and the variance of the production costs depend on the value of ϕ.

F.2 Moments

Table F.1: Targeted Moments

Description	Data	Model	% Dev. Sq	Description	Data	Model	% Dev. Sq
$\mathbb{E}\left[\sum_{i=1}^{I} \log Y_{in}\right]$	53.60	31.17	0.18	$\mathbb{E}\left[\sum_{i=1}^{I} \log Y_{in} \times 1\{G_i = 3\}\right]$	3.68	0.91	0.57
$\mathbb{E}\left[\sum_{i=1}^{I} \log Y_{in} \times \log GDPPC_i\right]$	-15.36	-5.16	0.44	$\mathbb{E}\left[\sum_{i=1}^{I} \log Y_{in} \times 1\{G_i = 4\}\right]$	4.32	1.63	0.39
$\mathbb{E}\left[\sum_{i=1}^{I} \log Y_{in} \times \log Population_i\right]$	39.07	28.90	0.07	$\mathbb{E}\left[\sum_{i=1}^{I} \log Y_{in} \times 1\{G_i = 5\}\right]$	10.40	3.41	0.45
$\mathbb{E}\left[\sum_{i=1}^{I} \log Y_{in} \times \log RoadDens_i\right]$	6.79	4.68	0.10	$\mathbb{E}\left[\sum_{i=1}^{I} \log Y_{in} \times 1\{G_i = 6\}\right]$	7.18	7.72	0.01
$\mathbb{E}\left[\sum_{i=1}^{I} \log Y_{in} \times \log DistHome_i\right]$	-144.56	-118.31	0.03	$\mathbb{E}\left[\sum_{i=1}^{I} \log Y_{in} \times 1\{G_i = 2\} \times Home_{in}\right]$	9.18	8.74	0.00
$\mathbb{E}\left[\sum_{i=1}^{I} \log Y_{in} \times \log Land_i\right]$	54.61	29.00	0.22	$\mathbb{E}\left[\sum_{i=1}^{I} \log Y_{in} \times 1\{G_i = 3\} \times Home_{in}\right]$	0.08	0.08	0.01
$\mathbb{E}\left[\sum_{i=1}^{I} \log Y_{in} \times Home_{in}\right]$	20.61	16.30	0.04	$\mathbb{E}\left[\sum_{i=1}^{I} \log Y_{in} \times 1\{G_i = 4\} \times Home_{in}\right]$	0.33	0.23	0.10
$\mathbb{E}\left[\sum_{i=1}^{I} D_{in}\right]$	5.26	4.37	0.03	$\mathbb{E}\left[\sum_{i=1}^{I} \log Y_{in} \times 1\{G_i = 5\} \times Home_{in}\right]$	6.58	3.41	0.23
$\mathbb{E}\left[\sum_{i=1}^{I} D_{in} \times \log GDPPC_i\right]$	-1.67	-0.92	0.20	$\mathbb{E}\left[\sum_{i=1}^{I} \log Y_{in} \times 1\{G_i = 6\} \times Home_{in}\right]$	3.74	3.49	0.00
$\mathbb{E}\left[\sum_{i=1}^{I} D_{in} \times \log Population_i\right]$	3.80	3.78	0.00	$\mathbb{E}\left[\sum_{i=1}^{I} D_{in} \times 1\{G_i = 2\}\right]$	2.09	2.31	0.01
$\mathbb{E}\left[\sum_{i=1}^{I} D_{in} \times \log RoadDens_i\right]$	0.63	0.59	0.00	$\mathbb{E}\left[\sum_{i=1}^{I} D_{in} \times 1\{G_i = 3\}\right]$	0.38	0.15	0.37
$\mathbb{E}\left[\sum_{i=1}^{I} D_{in} \times \log DistHome_i\right]$	-13.79	-13.65	0.00	$\mathbb{E}\left[\sum_{i=1}^{I} D_{in} \times 1\{G_i = 4\}\right]$	0.44	0.27	0.14
$\mathbb{E}\left[\sum_{i=1}^{I} D_{in} \times \log Land_i\right]$	5.40	4.10	0.06	$\mathbb{E}\left[\sum_{i=1}^{I} D_{in} \times 1\{G_i = 5\}\right]$	1.01	0.41	0.35
$\mathbb{E}\left[\sum_{i=1}^{I} D_{in} \times Home_{in}\right]$	1.99	1.94	0.00	$\mathbb{E}\left[\sum_{i=1}^{I} D_{in} \times 1\{G_i = 6\}\right]$	0.63	0.92	0.22
$\mathbb{E}\left[\log Y_n^2\right]$	24.35	15.55	0.13	$\mathbb{E}\left[\sum_{i=1}^{I} D_{in} \times 1\{G_i = 2\} \times Home_{in}\right]$	0.94	1.12	0.03
$\mathbb{E}\left[\log D_n^2\right]$	2.16	1.90	0.01	$\mathbb{E}\left[\sum_{i=1}^{I} D_{in} \times 1\{G_i = 3\} \times Home_{in}\right]$	0.01	0.01	0.00
$\mathbb{E}\left[\log Y_n\right]$	4.30	3.43	0.04	$\mathbb{E}\left[\sum_{i=1}^{I} D_{in} \times 1\{G_i = 4\} \times Home_{in}\right]$	0.03	0.03	0.00
$\mathbb{E}\left[\log D_n\right]$	1.03	1.13	0.01	$\mathbb{E}\left[\sum_{i=1}^{I} D_{in} \times 1\{G_i = 5\} \times Home_{in}\right]$	0.63	0.41	0.12
$\mathbb{E}\left[\log Y_n \times \log D_n\right]$	6.45	4.33	0.11	$\mathbb{E}\left[\sum_{i=1}^{I} D_{in} \times 1\{G_i = 6\} \times Home_{in}\right]$	0.32	0.35	0.01
$\mathbb{E}\left[\sum_{i=1}^{I} 1\{\log D_n = 0\}\right]$	0.38	0.17	0.30	$\mathbb{E}\left[\log Y_{in} \times 1\{Max\}\right]$	10.80	9.93	0.01
$\mathbb{E}\left[\sum_{i=1}^{I} 1\{\log D_n < log(3)\}\right]$	0.54	0.45	0.03	$\mathbb{E}\left[\log Y_{in} \times 1\{Max\} - \log Y_{in} \times 1\{2nd\}\right]$	0.71	1.53	1.31
$\mathbb{E}\left[\sum_{i=1}^{I} 1\{\log D_n < log(6)\}\right]$	0.74	0.78	0.00	$\mathbb{E}\left[\sum_{s=1}^{S}\sum_{i=1}^{I} \log Y_{in}^{(s)}\left(\frac{1\{Flood_{in}^{(s)}=1\}}{\sum_{s=1}^{S}1\{Flood_{in}^{(s)}=1\}} - \frac{1\{Flood_{in}^{(s)}=0\}}{\sum_{s=1}^{S}1\{Flood_{in}^{(s)}=0\}}\right)\right]$	-0.34	-0.42	0.06
$\mathbb{E}\left[\sum_{i=1}^{I} 1\{\log D_n > log(11)\}\right]$	0.13	0.08	0.18	$\mathbb{E}\left[\sum_{s=1}^{S}\sum_{i=1}^{I} \log Y_{in}^{(s)}\left(\frac{1\{100YFlood_{in}^{(s)}=1\}}{\sum_{s=1}^{S}1\{100YFlood_{in}^{(s)}=1\}} - \frac{1\{Flood_{in}^{(s)}=0\}}{\sum_{s=1}^{S}1\{Flood_{in}^{(s)}=0\}}\right)\right]$	-0.69	-0.29	0.34
$\mathbb{E}\left[\sum_{i=1}^{I} \log Y_{in} \times 1\{G_i = 2\}\right]$	21.42	15.80	0.07	$\mathbb{E}\left[\sum_{s=1}^{S}\sum_{i=1}^{I} \log Y_{in}^{(s)}\left(\frac{1\{10YFlood_{in}^{(s)}=1\}}{\sum_{s=1}^{S}1\{10YFlood_{in}^{(s)}=1\}} - \frac{1\{Flood_{in}^{(s)}=0\}}{\sum_{s=1}^{S}1\{Flood_{in}^{(s)}=0\}}\right)\right]$	-0.28	-0.40	0.18

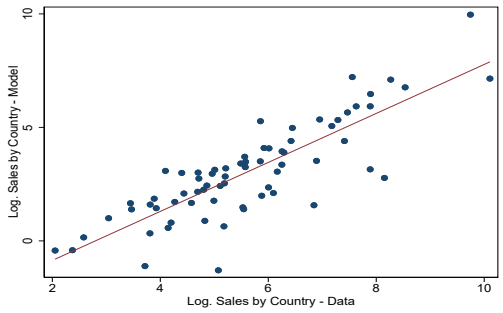
F.3 Model Fit

The structural model does a good job fitting the data. In Table F.1 in the Appendix, I show the value of the targeted moments in the data, in the model and the percentage deviation. It is clear that the model is underestimating the moments related to specific-location production. However, it is doing a good job at matching features of the distribution of total production at the firm-level. This is a manifestation of Jensen's inequality and might have to do with the distributional assumptions of the firm- and location-specific productivities. The model does a good job at matching the moments related to the geographic location of plants, and the features of the distributions of plants and total production at the firm level.

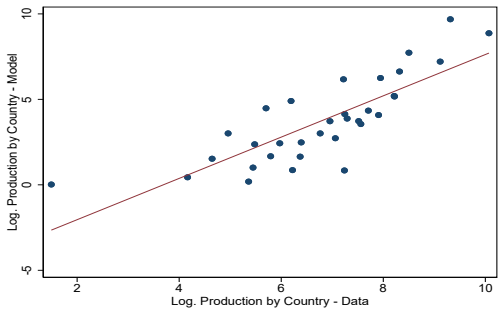
In Figure F.1, I explore the performance of the model in some moments that are not directly targeted. Specifically, I analyze how the model replicates the sales, plant location, and production at the country level, rather than at the smaller geographical units in which the firm decides. The relationship of the sales by country generated by the model and the data is very good, with a high R^2 and intercept close to 0 and a slope coefficient close to 1. Regarding production at the country level, the model does a good job at replicating production in big countries, but yields too little production in small countries.

Figure F.1: Model Fit - Sales and Production by Country

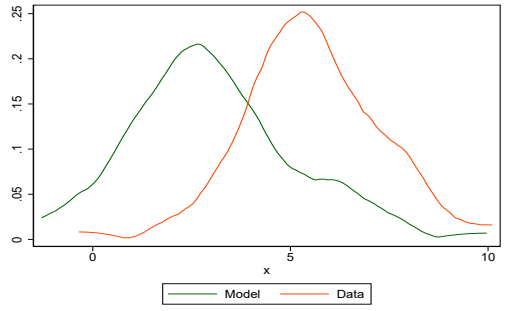
(a) Sales by Country



(b) Production by Country



(c) Density of Sales by Country



(d) Density of Production by Country

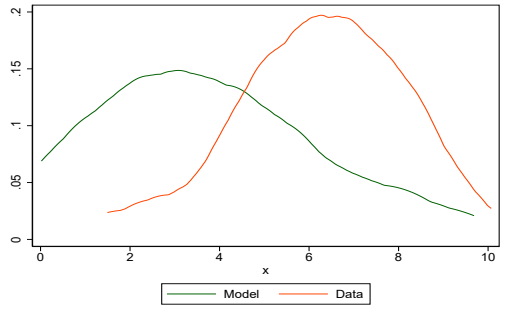
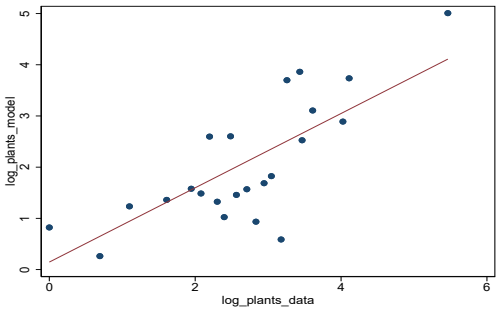


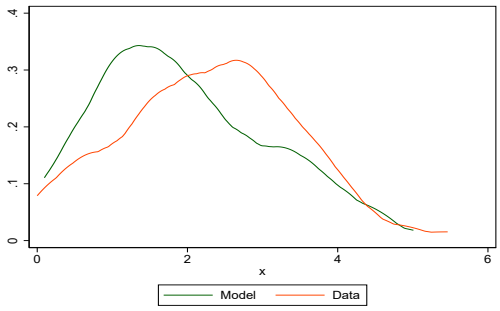
Figure F.2 shows that the model produces a geographic distribution of plants that resembles the one in the data. Finally, I show that the distribution of plants by firm is similar in the model and in the data. This is not surprising since I target percentiles of that distribution. However, it shows that at the current parameter estimates the model is not matching the distribution of firms with only one plant.

Figure F.2: Model Fit - Distribution of Plants by Firm and on Space

(a) Plants by Country



(b) Density of Plants by Country



(c) Density of Plants by Firm

