Expecting Floods: Firm Entry, Employment, and Aggregate Implications

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Abstract

Flood events and flood risk have been increasing in the past few decades and have important consequences on the economy. Using county-level and ZIP-code-level data during 1998–2018 from the U.S., we document that (1) increased flood risk has large negative impacts on firm entry, employment and output in the long run; (2) flood events reduce output in the short run while their impact on firm entry and employment is limited. Motivated by these findings, we construct a spatial equilibrium model to characterize how flood risk shapes firms' location choices and workers' employment, which we use to estimate the aggregate impact of increased flood risk on the economy. We find that flood risk reduced U.S. aggregate output by 0.52 percent in 2018, 80% of which stemmed from expectation effects and 20% from direct damages. We also apply our model to studying the distributional consequences and forecasting the impact of future changes in flood risk. Our results highlight the importance of considering the adjustment of firms and workers in response to risk in evaluating the consequences of natural disasters.

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1 Introduction

Floods are the most common natural disasters in many countries. In the past few decades, flood events have become more common, and flood risk has been increasing. For instance, according to the Federal Emergency Management Agency (FEMA), around 6 million Americans were living within a 100-year flood zone in the U.S. in 1998, and this number increased to 13 million in 2018. As global warming continues, the floodplains in the United States are expected to grow by approximately 45% by the end of this century (AECOM 2013). How does increasing flood risk shape the economy? In this paper, we study this question by focusing on the responses of firms and workers. Using data from the U.S., we study how both flood risk and flood events affect firms' location choices and workers' employment. We also quantify the aggregate implications of flood risk on the aggregate output.

While there exists a literature on the economic impact of floods,[1] few papers have investigated how the expectation of increasing flood risk shapes firm entry and employment, partly due to the lack of suitable data. In this paper, we leverage digitized national flood risk data over long time horizons and link them with county-level and ZIP-code-level information on firms and other outcomes during 1998–2018.

Using a standard design that controls for county fixed effects, year fixed effects and various confounding factors, we demonstrate two main empirical findings. First, increased flood risk has large negative impacts on firm entry, employment, and output in the long run. Specifically, one standard deviation increase in flood risk during the two decades studied reduced firm entry by 1.2%, employment by 1.2%, and real GDP by 2.4%. The impact on population size is also negative but the magnitude is smaller (0.8%) than that on employment. In addition, firm exits also declined with increased flood risk, implying that firms become less dynamic in a risky environment. Second, in contrast with the long-run impact of increased flood risk, yearly flood events have little impact on firm entry and employment in the short run, suggesting that these margins need time to adjust. Meanwhile, flood events reduced real GDP per capita, consistent with the fact that short-run floods affect the productivity of existing firms. Specifically, one standard deviation increase in the share of flooded areas reduced the real GDP in the same year by 0.2%.

One important empirical challenge is that the flood risk measure provided by FEMA likely suffers from measurement errors. Some data used in FEMA modeling were outdated

[1] Most of the literature has focused on actual flood events, while a couple of recent studies examine how flood risk affects housing prices (e.g., Hino and Burke 2020). See more discussions later when we discuss the related literature.

or inaccurate (Kousky 2018). In addition, because these FEMA maps are used to rate national flood insurance policies, there exist incentives for politicians and home owners to object map updates in order to avoid higher flood insurance rates (Flavelle et al. 2020). For our analysis, we assume that these risk measures are what have been observed by firms and workers and thus influence their decisions, despite possible measurement errors. To partially address the measurement concern, we employ an instrumental variable (IV) approach where we use the interaction between the state-level risk change (excluding one's own locality) and local geo-climatic conditions to predict local flood risk changes. Our IV estimates are similar in magnitude compared to those obtained from the fixed effects model. Our findings are also robust to using ZIP-code-level data that exploits finer variations.

Motivated by these findings, we construct a spatial equilibrium model built on canonical frameworks (McFadden 1978, Krugman 1980) to uncover the aggregate impact of flood risk. In our model, expecting flood risk, firms choose whether to enter a locality, while workers choose whether to relocate and how much labor to supply. For a given locality, realized floods affect firms' average productivity and workers' average amenity. The equilibrium wage links the decisions of firms and workers. In our model, flood risk affects the economy via three channels. The first is a *direct damage* channel that increases with higher flood risk. The second is an *employment* channel, where flood risk changes workers' location choices and reduces labor supply due to reduced real wages. The third is a *love of variety* channel, reflected by the number of firms that is also decreased by higher flood risk. We calibrate our model by targeting the responses of employment and population to flood risk through the indirect inference. For the non-targeted moments (output, firm entry, firm exit), our model-generate responses to flood risk are consistent with those based on micro data, suggesting that our model captures important forces in the economy.

Armed with our model, we conduct three sets of counterfactual analyses. First, we examine the aggregate impact of flood risk on the U.S. economy. We find that flood risk in 2018 caused a 0.52% decline in the aggregate output, out of which 0.11% was driven by the direct damage channel, 0.33% by the employment channel, and 0.08% by the variety channel. The latter two can be considered as consequences of expectation, which is four times more important than the direct damages. Second, we study the distributional impacts across regions. Indeed, the average decline masks wide regional variation: the loss of output in top 5% counties in the flood risk distribution (such as Cape May and New Jersey) was as high as 7–14% of county-level output. Third, we apply our model to a future scenario where the share of properties with flood risk increases by 4.5% between 2020 and 2050

(First-Street-Foundation 2021) and find that this increase would cause a 0.12% decline in aggregate output. Again, underlying this impact, the reduced employment in expectation of floods plays a more important role than the direct damages, which has not been emphasized by the existing literature.

Finally, we examine several extensions of our model, including assuming that creating a new firm requires a combination of labor and final goods, allowing for cross-regional trade flows, and considering both land and capital in firm production. These extensions generally predict a slightly larger impact of flood risk on the economy, and the small differences in magnitudes highlight the quantitative importance of the economic forces in our simplified baseline model.

Our study contributes to a burgeoning literature exploring the quantitative effect of climate changes on spatial economies (e.g., Costinot et al. 2016, Desmet et al. 2021, Alvarez and Rossi-Hansberg 2021).[2] Ours is particularly related to three studies on the aggregate effects of floods. Desmet et al. (2021) evaluate the economic cost of coastal flooding using global data and emphasize the role of migration and investments in local technology. Balboni (2019) studies the misallocation of infrastructure in the presence of coastal flooding driven by the risk of sea level changes. Lin et al. (2021) quantify the importance of agglomeration in explaining the increased new construction near coastal flood-prone areas. Our paper contributes to this literature in two aspects. First, whereas the previous literature has mostly focused on inundated land due to sea level rises, we exploit the new data (historic maps of flood zone designation) which incorporate overall flood risk, and we investigate the production damage of floods rather than land inundations. Second, we reconcile the quantitative analysis with our reduced-form evidence which highlights that firms' (and workers') responses to flood risk are different from the responses to actual floods.

Our micro-level evidence is built on recently digitized panel data on flood risk. Existing research on flood risk has been focusing on price effects. For instance, using the same data as ours, Hino and Burke (2020) show that the increased flood risk reduces property values by 1–2%. Both using household surveys to elicit flood risk perceptions, Mulder (2021) examines the welfare effect of improving the accuracy of the flood risk map, while Bakkensen and Barrage (2021) study residential sorting based on flood risk beliefs and the associated implications for coastal housing prices. Although we do not model housing explicitly, the housing price effect can be interpreted as the change in amenity in our model.[3]

[2] There is also a large literature developing macro models to evaluate climate changes on the national level (e.g., Nordhaus 1992, Acemoglu et al. 2012, Golosov et al. 2014, Barrage 2020).

[3] Our estimate is also comparable to theirs. Because housing prices can be interpreted as the present value

Our paper is also related to a growing empirical literature evaluating the economic consequences of natural disasters, especially those closely related to climate change (see Dell et al. (2014) for an overview).[4] We are particularly related to Kocornik-Mina et al. (2020) who use satellite nightlight data to evaluate the impacts of very large-scale floods spanning the globe's cities. Our findings on flood events are consistent with theirs: flood events reduce output but their impact does not last long, suggesting a fast recovery. In contrast, we show that flood risk can have long-run consequences, and the long-run impacts can be more severe than the short-run impacts, as they change firms' and workers' behavior. In addition to reduce-form evidence, our study *quantifies* the importance of considering both expectation effects and direct damages in evaluating the aggregate consequences of natural disasters.

This paper is organized as follows. Section 2 describes our data and measurement, and Section 3 demonstrates the reduced-form evidence, which leads to the model developed in Section 4. Section 5 takes the model to the data, and Section 6 performs counterfactual exercises to uncover the aggregate and distributional effects of flood risk. Section 7 concludes.

2 Data

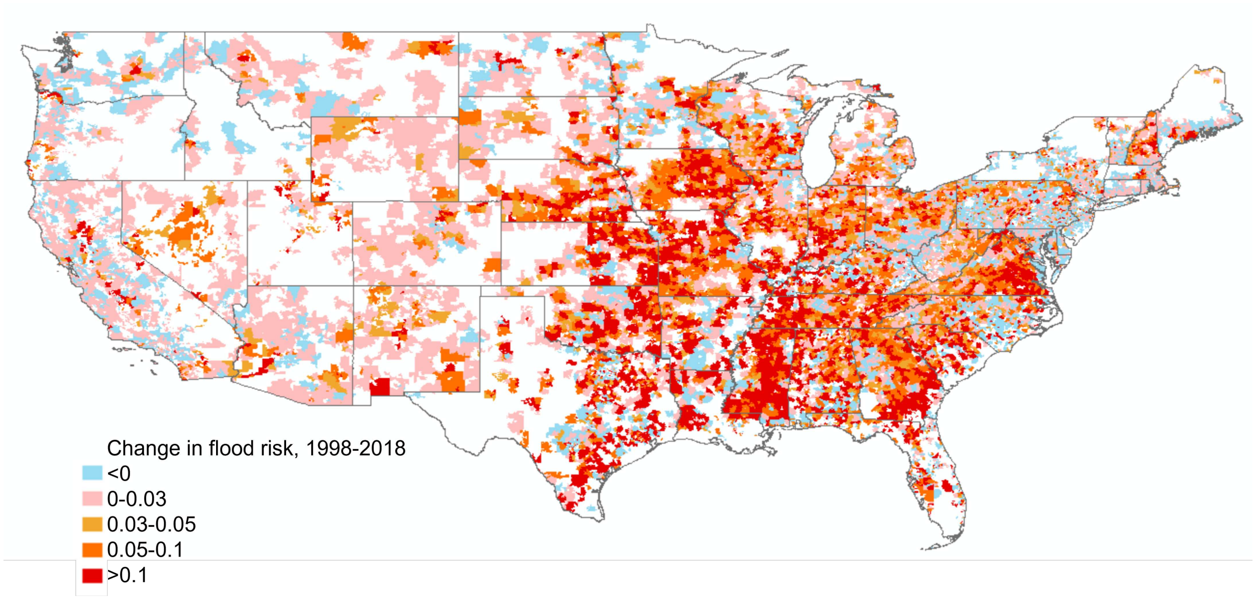
Flood Risk. We collect flood risk data from FEMA's historic and current designation maps of Special Flood Hazard Zones. The maps for historic flood zone designations, Q3, correspond to FEMA's Flood Insurance Rate Map in 1998. These maps assign flood zone designation at the polygon level and are used to determine national flood insurance premiums. The Special Flood Hazard Zone identified from these maps represents areas that will be inundated by the flood event with a one percent chance in any given year. In our analysis, we consider areas in Special Flood Hazard Zones as the FEMA floodplain (areas with flood risk). From the early 2000s, with new flood data and updated modeling methods, there were many FEMA map revisions. To exploit changes in FEMA's flood risk designations, we also obtain the current floodplain designation maps from FEMA's National Flood Hazard Layer (NFHL) in 2018.

Using map layers of FEMA's flood zone designations in 1998 and 2018, we calculate the share of land areas in FEMA's flood zones, separately for each county-level and ZIP-code-

of housing services and housing expenditures account for 30% of total consumers' expenditures (Serrato and Zidar 2016), Hino and Burke (2020)'s estimate implies that flood risks reduce workers' utility by 0.3–0.6% through housing damage, similar to our calibrated amenity loss of 0.2%.

[4] Recent studies include Gallagher (2014), Hsiang and Jina (2014), Deryugina (2017), Hsiang et al. (2017), and Tran and Wilson (2021), among others.

Figure 1: Change in Flood Risk, ZCTA-level, 1998-2018



Notes: white space in the map refers to the areas with either no official USPS delivery address or no flood map coverage.

level tabulation area in either year of 1998 and 2018.[5] We use this share of areas within flood zones as the flood risk measure. In Figure 1, we plot the change in flood risk from 1998 to 2018, at the ZIP code level. The figure shows that many counties experienced a significant increase in flood risk during our sample period. On average, the share of land areas in flood zones increased by 1.5 percentage points, with a 20-percentage-point increase in the 90th percentile across the distribution of ZIP-code-level flood risk changes.

One main concern about this flood risk measure is measurement error. As the FEMA maps are used to rate national flood insurance policies, there exist incentives for politicians and home owners to object map updates in order to avoid higher flood insurance rates. In addition, it has been long argued that some data used in FEMA modeling were outdated or inaccurate, and thus, these flood zones may not fully reflect actual flood risk (e.g., Kousky 2018, Flavelle et al. 2020). As these flood zones are the signals directly observed by firms, it is unclear how these measurement errors affect our findings *a priori*. We address this challenge using an instrument based on geo-climatic conditions to predict flood risk changes.

Flood Events. Similar to the existing literature (e.g., Kocornik-Mina et al. 2020), our spatial data on actual floods come from the Global Active Archive of Large Flood Events

[5]In our analyses, we winsorize this measure at the top and bottom to minimize measurement errors.

collected by the Dartmouth Flood Observatory. These data record the occurrence and severity of flood events across the globe and are available from 1985 to the present year.

Firm and Labor Outcomes. We are interested in the responses of both firms and workers. At the county level, for each year of our interest, we obtain the county-level numbers of establishment entrants and exits, based on data from the US Census's Business Dynamics Statistics. In this paper, we consider establishments as firms, as establishments are the basic units of production in the data, and distinguishing between multi-establishment and single-establishment firms is not the focus of our study. On the worker side, we obtain employment data from the US Census's Business Dynamics Statistics and prime-age population data from the Census series. Finally, we use county-level real GDP data provided by the Bureau for Economic Analysis. The summary statistics for these variables are presented in Panel A, Appendix Table A.1.

At the ZIP code level, we draw on the ZIP Codes Business Patterns (ZBP) to measure economic outcomes including the number of establishment, employment, and payrolls.[6]

Control Variables. County-level changes in economic performance may be driven by confounding factors other than flood risk. For example, changes in firm dynamics, employment and total output could reflect local demographic and economic factors such as trade exposure. To ensure the relationships of our interest are not driven by other county-level characteristics, we will control a set of county-level characteristics in our empirical analysis.[7] These characteristics include the share of female labor, manufacturing share of employment, and population density, and changes in China's import penetration ratio (see Appendix Table A.1 for a summary of these controls). We also allow for the impact of these characteristics to change over time in our regressions, as detailed below.

3 Reduced-form Evidence

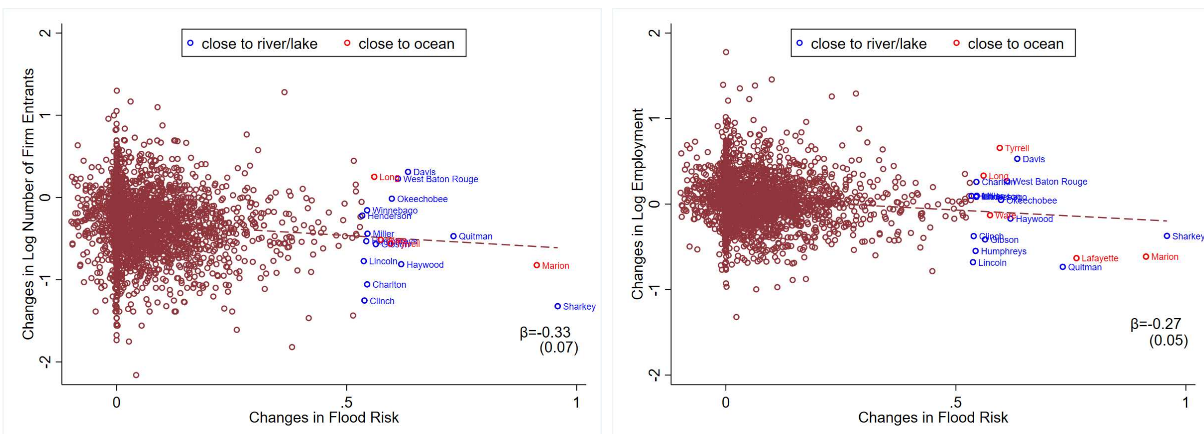
In this section, we present reduced-form results on the impact of flood risk and those of actual flood. We first explore the impact of flood risk on firms and employment, which is novel to the literature, by presenting motivational evidence in Section 3.1 and performing formal empirical analysis in Section 3.2. We then estimate the impact of actual flood events, which allows us to discipline the model parameters that governs direct damages of floods.

[6]The measures for population and firm exits are not available at the ZIP code level from the ZBP.
[7]We follow Autor et al. (2013) in constructing these controls.

3.1 The Impact of Flood Risk: Motivation and Research Design

As motivational evidence, we examine how flood risk changes correlate with changes in firm entry and employment in the raw data. In Figure 2a, we plot county-level changes in the number of firm entrants between 1998 and 2018 against county-level changes in flood risk. The scatter plot reveals a significant negative correlation. Similarly, as shown in Figure 2b, we also observe a county-level negative correlation between flood risk and employment changes. In the raw data, one standard deviation (7-percentage-point) increase in the share of land within FEMA's flood zones is associated with a decline of 2.3% in firm entry and a decline of 1.9% in employment. These figures also reveal that the counties that experienced the highest increases in flood risk are located close to rivers, lakes, or oceans.

Figure 2: Glance at the Raw Data



(a) Firm Entry **(b)** Employment

Notes: For the counties that experienced the highest increase in flood risk, we highlight them in red if they are coastal (e.g. Marion county, FL), and in blue if they are located close to a river or lake (e.g. Sharkey county, MS).

These correlations in the raw data suggest that increased flood risk deters firm entry and employment. However, these relationships may be confounded by other county-level characteristics. To formally examine the casual impacts of flood risk increase on firm entry, employment and other outcomes, we use a fixed effect framework that controls various confounding factors. Our baseline empirical specification is as follows:

$$logY_{i,t} = \alpha + \beta_1 FloodRisk_{i,t} + \sigma_i + \gamma_{s,t} + X_{i,t} + \beta_2 ActualFlood_{i,t} + \epsilon_{i,t}, \quad (1)$$

where $logY_{i,t}$ is log number of firm entrants (or other outcomes of interest) in locality i

(county or ZIP code) and year t. Our main independent variable $FloodRisk_{i,t}$ represents the percentage of land areas within FEMA's special flood zones in locality i and year t. Due to the data limits and our interest in the long-run impact of flood risk, we focus on two years' outcomes, $t = 1998$ and $t = 2018$.

The locality (county or ZIP code) fixed effects, σ_i, absorb any time-invariant locality characteristics that may correlate with flood risk and outcomes. State-by-year fixed effects, γ_{st}, capture the statewide economic growth or business cycle fluctuations. Additionally, the vector $X_{i,t}$ contains a set of county-level demographic and economic factors as described in Section 2, capturing other factors that may confound the relationship between flood risk and county-level outcomes. To separate the different effects of flood risk and actual flood events, we also control for $ActualFlood_{i,t}$, which is defined as the percentage of flooded areas in locality i in year t. Standard errors are clustered at the county level.

3.2 The Impact of Flood Risk: Empirical Findings

3.2.1 Fixed Effect Regressions

County-level Results. Panel A in Table 1 presents the county-level impact of flood risk on firm entry, firm exit, employment, population, and real GDP, respectively. The regressions in odd columns control for county fixed effects, state-by-year fixed effects, and control variables interacted with year fixed effects, whereas the regressions in even columns further control for the share of actual flooded areas in the corresponding year, given the concern that actual floods may drive the impact of flood risk. We find that the estimated impacts of flood risk are quite stable regardless of whether we control for the occurrence of actual floods.

We highlight three empirical findings. First, Column (2) shows that the increased flood risk negatively affected firm entry. In terms of the magnitude, a standard deviation (7-percentage-point) increase between 1998 and 2018 in flood risk reduced the number of firm entrants in 2018 by 1.2%, and a county whose flood risk increase lied in the 90th percentile among all counties would on average experience a reduction of 3.3% in firm entry. Accompanying the decline in firm entry, Column (4) shows that firm exits also decreased with flood risk, with a smaller magnitude than the effect on firm entry. Even though natural disasters are typically associated with more closure of production facilities (as we show in Section 3.3), the decline in firm exits likely reflects the impact of fewer firms and declined firm dynamism.

Second, Columns (6) and (8) together indicate that an increase in flood risk significantly lowered employment and to a smaller magnitude reduced population. Specifically, a standard deviation (7-percentage-point) increase in flood risk reduced population by 0.8 percent and employment by 1.2 percent. The population change mainly reflects households' relocation given that we control for actual floods and focus on prime-age population. Our finding on the population decline in response to flood risk is natural, as people tend to move away from the risky areas, which has been recognized as essential in understanding the long-run mitigation of natural disasters (e.g., Desmet et al. 2021). Furthermore, our results indicate that adjustments of employment to flood risk are larger than population adjustments, suggesting that the remaining population may also adjust their employment choices. Guided by these empirical findings, we will embed migration and endogenous labor supply into our model.

Finally, along with the decline in firm dynamism and employment, Column (10) shows that real GDP decreased by 2.4% with a standard deviation increase in flood risk.

ZIP-Code-Level Results. Next, we use the ZIP-code-level data, exploiting finer spatial variations in the changes of flood risk status and firm-level outcomes. Because information on firm entry, exit, and real GDP is not available on the ZIP code level, we instead focus on two related variables, namely the number of establishments and annual payrolls. We also omit results about population due to the lack of data at the ZIP-code level. We use similar specification as before, where we control for ZIP-code-level fixed effects, state-by-year fixed effects, control variables and actual floods. Panel B of Table 1 shows that focusing on a finer geographic variations, the impact of flood risk is fairly similar in magnitude to the county-level results: an increase in flood risk significantly decreased the number of firms, total employment, and total payrolls.

Additional Robustness Check. It is worth noting that FEMA historic Q3 maps do not provide information for a subset of counties. We treat the flood risk in these unreported areas as zero, since firms and households do not observe any risk signal from FEMA. Alternatively, Appendix Table A.2 performs our baseline regression (1), using the counties with available FEMA flood maps for both 1998 and 2018. We find that the estimated impacts of flood risk are qualitatively similar to our baseline results, with slightly larger magnitudes. To be conservative, we use our baseline estimates to calibrate the quantitative model.

Table 1: The Impact of Long Run Change in Flood Risk: Fixed Effects Estimates

Panel A: County Level

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	log(Entry)		log(Exit)		log(Employment)		log(Population)		log(Output)[a]	
Flood risk	-0.172**	-0.173**	-0.119*	-0.119*	-0.171***	-0.171***	-0.114***	-0.115***	-0.337***	-0.337***
	(0.079)	(0.079)	(0.072)	(0.072)	(0.059)	(0.059)	(0.041)	(0.041)	(0.072)	(0.072)
Observations	5188	5188	5174	5174	5280	5280	5282	5282	5222	5222
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State×Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
OtherControls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ActualFlood		Yes		Yes		Yes		Yes		Yes
ymean	4.080	4.080	4.022	4.022	9.03	9.03	9.914	9.914	13.73	13.73

Panel B: ZIP Code Level

	(1)	(2)	(3)	(4)	(5)	(6)
	log(Establishment)		log(Employment)		log(Payroll)	
Flood risk	-0.233***	-0.234***	-0.240***	-0.242***	-0.221***	-0.223***
	(0.040)	(0.040)	(0.066)	(0.066)	(0.072)	(0.072)
Observations	43330	43330	41032	41032	41034	41034
ZCTA FE	Yes	Yes	Yes	Yes	Yes	Yes
State×YearFE	Yes	Yes	Yes	Yes	Yes	Yes
OtherControls	Yes	Yes	Yes	Yes	Yes	Yes
ActualFlood		Yes		Yes		Yes
ymean	4.330	4.330	6.611	6.611	9.964	9.964

Notes: a.We use county-level GDP in 2001 instead of 1998 for columns (9) and (10) since the BEA county-level GDP data starts from 2001. The main independent variable $FloodRisk_{i,t}$ represents the percentage of land area within FEMA's special flood zone in locality i and year t. We are interested in the long-run impact of flood risk and thus focus on t being 1998 and 2018. All regressions control for locality fixed effects, state-by-year fixed effects, and a rich set of demographic and economic controls. Firm entry, exit and population data are not available at the ZCTA level. Standard errors are clustered at the locality level (county or ZIP code).

3.2.2 IV Estimation

As discussed in Section 2, the flood risk measures may reflect potential political economy factors rather than actual risk. To check whether such measurement errors lead to a sizable bias in our estimates, we implement an instrumental variable approach. Specifically, we construct a Bartik-type instrument, using the interaction of average changes in flood risk in the rest of the state and a county's own geo-climatic features (satellite-based measures of yearly average temperature, cumulative rainfall and evaporation) to predict a county's risk change. Intuitively, average changes in flood risk in the rest of the state proxies general risk change in a broad region, whereas this general change likely matters more for counties with certain geo-climatic conditions such as heavy rainfalls. In addition, we also control for the cumulative flooded area from all flooding events that have occurred during our sample period for each county, in case these geo-climatic features are correlated with past floods.

Table 2 reports the results from the IV regressions. Overall, we find that the IV estimates are comparable in magnitude to our previous fixed effects estimates. According to these estimates, one standard deviation increase in flood risk reduced county-level firm entry by 1.2 percent, employment by 1.4 percent, and real GDP by 2.2 percent. Thus, even though the flood risk measures are likely to reflect some unobserved potential political economy factors, there does not seem to be a large bias in our fixed effect estimates.

To check the validity of our IV approach, we follow Goldsmith-Pinkham et al. (2020) to perform a placebo (pre-trend) test. Instead of using the outcomes between 1998 and 2018, we now look at the effect of flood risk changes between 1998–2018 on the changes in firm dynamics and other county-level outcomes between 1990–1998. Intuitively, if the negative impact of flood risk changes on economic outcomes during our sample period is driven by other omitted local economic characteristics, these negative impacts may have already occur in earlier periods. We find that this is not the case, as shown in Appendix Table A.3:[8] estimates from the placebo tests are much smaller in magnitude and not significant, suggesting that our instrument does not reflect omitted county-level characteristics.

3.3 The Impacts of Flood Events

We now proceed to understand the direct damages of actual floods, examining the impact of actual floods on the same outcomes as above. This exercise not only confirms the negative

[8] We do not examine real GDP in the placebo test because county-level GDP data were not available before 1998.

Table 2: The Impact of Long Run Change in Flood Risk: Change-on-Change Estimates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Δlog(Entry)		Δlog(Exit)		Δlog(Employment)		Δlog(Population)		Δlog(Output)	
ΔFlood risk	-0.188**	-0.167**	-0.134*	-0.097	-0.183***	-0.193***	-0.123***	-0.136***	-0.328***	-0.308***
	(0.080)	(0.085)	(0.073)	(0.079)	(0.060)	(0.065)	(0.042)	(0.053)	(0.070)	(0.074)
Observations	2594	2593	2587	2586	2640	2639	2641	2640	2611	2610
KP F stat		63		66		66		65		65
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cum. Floods	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Specification	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV

Notes: Outcome variables are changes in log terms. The main independent variable $D.FloodRisk_{i,t}$ represents changes in the percentage of land area within FEMA's special flood zone in locality i between years 1998 and 2018. "IV" represents our instrumental variable approach, using the interaction of average changes in flood risk in the rest of the state and a county's own geo-climatic features as instruments. All regressions control for state fixed effects, cumulative flood area and a rich set of demographic and economic controls. We also report the first-stage Standard errors are clustered at the county level.

damage of floods as similarly shown by recent studies (Kocornik-Mina et al. 2020), but also allows us to discipline the parameters that govern direct damages of floods in the model.

We employ yearly information on flood events using data from the Dartmouth Flood Archives and estimate the impact of an actual flood on economic outcomes in the same year (we will also discuss lagged effects below), similar to Kocornik-Mina et al. (2020). Our specification is as follows:

$$logY_{i,t} = \alpha + \beta_1 Flood_{i,t} + \sigma_i + \gamma_{s,t} + X_{i,t} + +\epsilon_{i,t} \tag{2}$$

where again, $logY_{i,t}$ is log number of firm entrants (or other outcomes of interest) in county i and year t. Our main independent variable $Flood_{i,t}$ represents the percentage of county areas being flooded in county i and year t. Similar as before, we control for county fixed effects (σ_i), state-by-year fixed effects (γ_{st}), as well as the set of county-level demographic composition and China's import penetration ratios by year (X_{it}). Because county-level GDP data, business dynamics, and flooding data are available for the period 2001–2018, we thus use a balanced panel of county-level outcomes over these 18 years for estimation. Standard errors are clustered at the county level.

Table 3 reports the results. Overall, we find that the impacts of actual floods are vastly different from those of flood risk. As shown in Table 3, actual floods had a negligible impact on firm entry, firm exit, employment, or population. However, actual floods did decrease actual real GDP. As shown in Column (10), a standard deviation increase (0.4) in the share of

Table 3: The Impact of Short Run Actual Floods: Fixed Effects Estimates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	log(Entry)		log(Exit)		log(Employment)		log(Population)		log(Output)	
Flood share	0.002	0.001	0.002	0.003	-0.000	-0.001	0.001***	0.001***	-0.005***	-0.005***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.001)	(0.001)	(0.000)	(0.000)	(0.002)	(0.002)
Observations	51595	50782	51584	50931	53195	52666	53244	52683	52320	51816
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State×Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Initial Controls		Yes		Yes		Yes		Yes		Yes
ymean	4.018	4.036	3.979	3.991	8.864	8.870	9.816	9.825	13.66	13.67

Notes: Outcome variables are changes in log terms. The main independent variable $Floodshare_{i,t}$ represents changes in the percentage of land area flooded in county i, year t. We are interested in the short run impact of yearly floods and the sample period is 2001-2018. All regressions control for county fixed effects, state-by-year fixed effects, and a rich set of initial control by year trends. Standard errors are clustered at the county level.

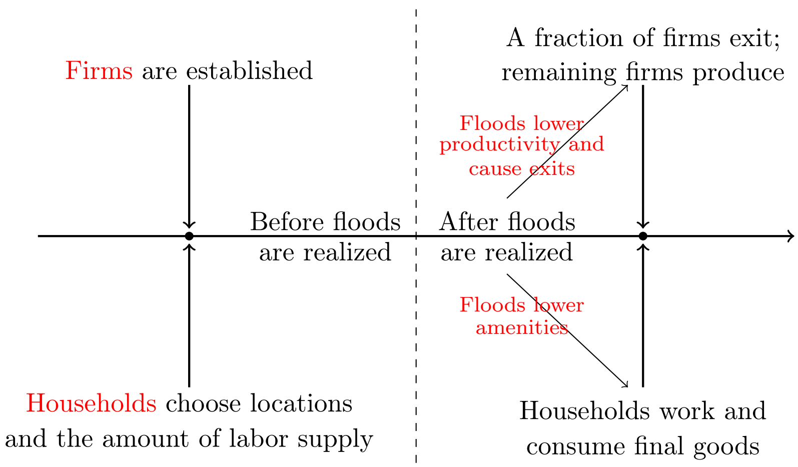
flooded areas in a year significantly lowered real GDP by 0.2%. This magnitude is consistent with that found in the recent papers (e.g., Henderson et al. 2012, Kocornik-Mina et al. 2020). Also in line with these papers, we find that the impact is primarily driven by the current year's flood shocks. As shown in Appendix Table A.4, lagged flood shocks from the previous year incur negligible real GDP losses in the current year. Given these findings, in the model developed in the next section, the impact of actual floods mainly unfolds through the negative productivity impact.

4 Model

Our reduced-form results demonstrate that increased flood risk reduces firm dynamism in the long run: firm entry declines significantly and firm exits follow to some extent. Increased firm risk also reduces employment and decreases population to a lesser extent. These negative impacts of flood risk are also reflected by a decline in real GDP. The actual flood events, in contrast, mainly affects short-run productivity and has limited impacts on firm and employment adjustments. In light of these patterns, we construct a model where firms and workers consider both flood risk and actual floods in their decisions.

We consider an economy with totally M regions (indexed by m). The production in each region resembles Krugman (1980) with free entry of firms. The total amount of households is normalized to $\bar{L} = 1$. Households choose locations and labor supply to maximize their utility. We introduce flood risk as follows. Let $S = \{s_1, s_2, ...\}$ be the set of possible states of nature. Each state s is characterized by probability $\Pr(s)$ and the corresponding vector of flooding events, $\{\xi_1(s), \xi_2(s), ..., \xi_M(s)\}$, where binary variable $\xi_m(s) \in \{0, 1\}$ indicates the occurrence of flooding. Following macro models on climate changes (e.g., Nordhaus 1992, Acemoglu et al. 2012, Golosov et al. 2014, Barrage 2020), we consider that actual flood events affect firms' average productivity and workers' average amenities within the region. Flood events may also destruct a portion of firms. Before the shocks are realized, households make location and labor supply decisions, and firms make entry decisions. Once shocks are observed, production and consumption occur. We display the timing of the model in Figure 3 and will describe each activity in detail below.

Figure 3: Timing in the Model



4.1 Production

In region m, there is a composite final good, which is composed of differentiated varieties, according to the CES technology,

$$Y_m(s) = \left(\int_{\omega \in \Omega_m(s)} y(\omega, s)^{\frac{\sigma-1}{\sigma}} d\omega \right)^{\frac{\sigma}{\sigma-1}}, \tag{3}$$

where $\Omega_m(s)$ is the set of varieties produced in region m and state s, and we abstract from trade in our baseline model and consider it in our extensions. $\sigma > 1$ is the elasticity of substitution across varieties. The final good is used for consumption. The price index is thus:

$$P_m(s) = \left(\int_{\omega \in \Omega_m(s)} p(\omega, s)^{1-\sigma} d\omega \right)^{\frac{1}{1-\sigma}}, \tag{4}$$

where $p(\omega, s)$ is the price level of the variety ω in state s.

Following Krugman (1980), establishing a firm in region m requires f_m units of labor. Each firm obtains a blueprint for producing a differentiated variety and is engaged in monopolistic competition. To produce output, each firm uses $l_m^d(s)$ units of labor according to a constant-returns-to-scale production technology:

$$y_m(s) = A_m(s) l_m^d(s). \tag{5}$$

$A_m(s)$ denotes productivity level in state s. We assume $A_m(s) = \bar{A}_m \exp(-\delta \xi_m(s))$, where δ determines the extent to which firm productivity levels are affected by flooding events. We follow the growth literature (e.g., Atkeson and Burstein 2010) to assume that an exogenous rate $\kappa(s) = \bar{\kappa} \exp(\delta_\kappa \xi_m(s))$ of firms exit before production. The parameter $\bar{\kappa}$ captures various factors (e.g., lawsuits, managerial shocks) that lead firms to cease operation, and δ_k governs the extent to which a portion of firms are destructed by floods.

Under monopolistic competition, the optimal price charged by a firm in region m is $\tilde{\sigma} W_m(s)/A_m(s)$, where $\tilde{\sigma} = \frac{\sigma}{\sigma-1}$ is the constant mark-up, and $W_m(s)$ is the wage rate in region m. Hence, the total profits for a firm are:

$$\pi_m(s) = \frac{1}{\sigma} \left(\tilde{\sigma} \frac{W_m(s)}{A_m(s)} \right)^{1-\sigma} P_m(s)^\sigma Y_m(s) = \frac{W_m(s) l_m^d(s)}{\sigma - 1}. \tag{6}$$

The first equality shows the total profit is a portion $\frac{1}{\sigma}$ of the total revenue. The second equality comes from that the cost-to-profit ratio is $(\sigma - 1)$.

Firms are established before shocks are observed. In equilibrium, free entry implies that the expected costs of establishing a firm equal the expected profits of a firm for each region:

$$\sum_s \Pr(s) W_m(s) f_m = \sum_s \Pr(s) \left(1 - \kappa(s)\right) \pi_m(s). \tag{7}$$

4.2 Households

We assume that the household's utility in region m is:

$$\begin{aligned} &U_m(s) = v_m B_m(s) \left(c_m(s) l_m - \psi_m \frac{l_m^{1+1/\phi_L}}{1 + 1/\phi_L} \right), \\ &s.t. \ P_m(s) c_m(s) \leq W_m(s). \end{aligned} \tag{8}$$

Households are identical except for heterogeneous location preferences $\{v_m\}$, distributed according to a Fréchet distribution $G(v) = \exp(-v^{-\phi_M})$ and i.i.d. across regions and households. Location preferences are used in the literature (e.g., McFadden 1978) to tractably generate labor mobility across regions as shown below. We consider amenities $B_m(s) = \bar{B}_m^{1/\phi_M} \exp(-\eta\xi_m(s))$ as proportional adjustments to utility from consumption and labor disutility (e.g., Fajgelbaum et al. 2018, Bryan and Morten 2019). The parameter $\eta > 0$ captures negative amenity shocks due to floods, as floods may lead to discomfort and disorder in public services. $c_m(s)$ denotes expenditures per labor on final goods in state s.

Similar to import competition studied in Autor et al. (2013), we find that flood risk has a larger impact on employment than on population. This finding indicates that changes in local employment is not only due to households' relocation, but may also reflect households' endogenous choices of labor supply. Hence, instead of assuming one unit of labor per household, we introduce a positive labor supply elasticity $\phi_L > 0$.[9] For analytical tractability, we assume that labor supply l_m is decided before shocks happen, consistent with our empirical evidence that employment responses are mainly driven by flood risk instead of actual floods. One micro-foundation is that in the presence of labor market frictions, job search takes time and can not be completed immediately (Mortensen and Pissarides 1994, Pissarides 2000).

Each household chooses its location and labor supply to maximize its expected utility before shocks are observed, $\max_{m,l_m} \sum_s \Pr(s) U_m(s)$. In equilibrium, the endogenous labor supply l_m and the population share Λ_m in region m are given by:[10]

$$l_m = \left(\sum_s \Pr(s) \frac{W_m(s)}{\psi_m P_m(s)} \right)^{\phi_L}, \tag{9}$$

$$\Lambda_m = \frac{\left[\sum_s \Pr(s) B_m(s) \psi_m l_m^{1+1/\phi_L} \right]^{\phi_M}}{\sum_{m'} \left[\sum_s \Pr(s) \psi_{m'} B_{m'}(s) l_{m'}^{1+1/\phi_L} \right]^{\phi_M}}. \tag{10}$$

We relegate the proof to Appendix B.1. Hence, ϕ_L and ϕ_M jointly govern the responses of labor supply per household and the number of households to changes in real wages and

[9] Alternatively, we can assume employment and non-employment sectors in each region and allow for households to choose between locations and sectors. This alternative setting would lead to very similar results, if in response to changes in real consumption, the elasticity of location choices is different from the elasticity of sector choices (e.g., Adao et al. 2018).

[10] The first-order condition implies that $l_m = \left(\sum_s \Pr(s) \frac{B_m(s)}{\sum_s \Pr(s) B_m(s)} \frac{W_m(s)}{\psi_m P_m(s)} \right)^{\phi_L}$, where $\frac{B_m(s)}{\sum_s \Pr(s) B_m(s)} \approx 1$ as η is small. Numerically, we find that this simplification has little effect on the quantitative results.

amenities across regions. In our quantitative analysis, we will discipline these two parameters using our reduced-form evidence on the region-level responses of population and employment to shifts in flood risk. The total supply of labor in region m is given by $L_m = \Lambda_m l_m \bar{L}$.

4.3 Equilibrium

Let N_m be the amount of firm entrants in region m before shocks happen, and define $N_m(s) = N_m(1-\kappa(s))$ as the number of actively operating firms, reflecting the effects of firm exits. The market clearing for final goods in region m requires that households' total consumption equals the total production:

$$P_m(s)L_m c_m(s) = P_m(s)Y_m(s). \tag{11}$$

The labor market clearing in region m requires:

$$N_m(s)l_m^d(s) + N_m f_m = L_m. \tag{12}$$

which, combined with equation (7), implies that $N_m = \frac{L_m}{\sigma f_m}$ and $l_m^d(s) \equiv \frac{(\sigma-1)f_m}{1-\kappa(s)}$.

Now, we define the general equilibrium of our model:

Definition 1 *The general equilibrium consists of regional labor supply* $\{\Lambda_m, l_m\}$ *and the amount of firms* N_m*, and in each state of nature* s*, households' consumption* $c_m(s)$*, firms' employees* $l_m^d(s)$*, and aggregate price and quantity variables* $\{P_m(s), Y_m(s), W_m(s)\}$*. These variables satisfy:*
(a) before shocks are realized, regional supply of households $\{\Lambda_m, l_m\}$ *is determined by households' expected utility maximization as given by equations (9)–(10);*
(b) before shocks are realized, the amount of firms N_m *in each region is determined by free-entry conditions in equation (7);*
(c) in state s*, firms' choices of employees* $l_m^d(s)$ *are determined by the maximum profits given by equations (6);*
(d) in state s*, the quantity* $Y_m(s)$ *clears the goods market for each region, as shown in equations (11), with* $P_m(s)$ *being the aggregate price index given by equation (4); and*
(f) in state s*, wages* $W_m(s)$ *clear each region's labor market, as shown in equation (12).*

Proposition 1 (Uniqueness of Equilibrium) *If* $\left|\frac{\phi_M(\phi_L+1)}{\sigma-1-\phi_L}\right| \leq 1$*, the equilibrium is unique if it exists.*

Proof: See Appendix B.2. □

Proposition 1 specifies the condition for uniqueness of the equilibrium, and this condition is satisfied by our calibration in the quantitative analysis.

4.4 Main Forces at Work

We now show how flood risk affects aggregate productivity. Let $r_m = \sum_s \Pr(s)\xi_m(s)$ be the probability of the flood shock occurring in region m. In our model, combining equations (3), and (7), (12), aggregate output can be written as:

$$Y_m(s) = \left(N_m(s)(A_m(s)l_m^d(s))^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}} \propto A_m(s)N_m(s)^{\frac{1}{\sigma-1}}L_m. \tag{13}$$

Because the real wage per labor is $\frac{Y_m(s)}{L_m}$, we can rearrange labor supply in equation (9) as:

$$l_m \propto \left(\sum_s \Pr(s)A_m(s)N_m(s)^{\frac{1}{\sigma-1}}\right)^{\phi_L} \tag{14}$$

The parameter $\frac{1}{\sigma-1}$ captures the agglomeration force due to more varieties. To make progress analytically, we focus on changes in flood risk in a region that accounts for a small share of the national population and thus abstract from general-equilibrium responses in households' utility in other regions. The population share in equation (10) is

$$\Lambda_m \propto \left(\sum_s \Pr(s)B_m(s)l_m^{1+1/\phi_L}\right)^{\phi_M}. \tag{15}$$

Finally, noting the firm mass $N_m(s) \propto L_m(1-\kappa(s))$ and the total labor supply $L_m \propto \Lambda_m l_m$, we can analytically characterize the responses of endogenous variables $\{Y_m(s), l_m, \Lambda_m, N_m(s), L_m\}$ to changes in flood risks. Denote $\hat{x} = log(x'/x)$ as the proportional change in variable x.

Proposition 2 (Responses to Changes in Flood Risks) *For a small region m, in response to a change in flood risk, the changes in labor supply, population share, total employment, firm count, and average output are:*

$$d\hat{l}_m = -\phi_L \frac{\delta + \frac{1}{\sigma-1}\bar{\kappa}\delta_\kappa + \frac{1}{\sigma-1}\phi_M\eta}{1-\frac{1}{\sigma-1}(\phi_L + (\phi_L+1)\phi_M)} dr_m, \tag{16}$$

$$d\hat{\Lambda}_m = \phi_M\left[(1+1/\phi_L)d\hat{l}_m - \eta dr_m\right], \tag{17}$$

$$d\hat{L}_m = d\hat{l}_m + d\hat{\Lambda}_m, \tag{18}$$

$$d\widehat{\mathbb{E}N}_m = d\hat{L}_m - \bar{\kappa}\delta_k dr_m, \tag{19}$$

$$d\widehat{\mathbb{E}Y}_m = -\delta dr_m + d\hat{L}_m + \frac{1}{\sigma - 1} d\widehat{\mathbb{E}N}_m, \tag{20}$$

where $\mathbb{E}N_m = \sum_s Pr(s)N_m(s)$ *and* $\mathbb{E}Y_m = \sum_s Pr(s)Y_m(s)$ *is the average firm count and output across states of nature.*

Proof: See Appendix B.3. □

Equation (16) shows how labor supply per household responds to changes in flood risk. When the chances of flooding are higher, the stronger damages on firms' productivity, firm count, and amenity reduce households' utility. If the agglomeration force is small, $\frac{1}{\sigma-1}(\phi_L + (\phi_L + 1)\phi_M) < 1$, the labor supply would decrease with higher flood risk. In this sense, our model captures the "immobile labor" (Autor et al. 2013), as households respond to the shock by reducing labor supply instead of moving to other regions. Equation (17) shows how a higher flood risk induces regional relocation, as it reduces amenities and real consumption. The change in the region-level total labor supply in equation (18) includes both regional relocation and the change in the labor supply per household.

Equations (19)–(20) display how the production side responds to higher flood risk. Less labor supply and larger damages on firm count translate to fewer firms. The average aggregate output changes due to three factors. First, the average direct damage of flooding increases with higher flood risk, which we term the *direct damage* channel. Second, higher flood risk induces lower employment and reduce output, which we call the *employment* channel. As discussed earlier, employment changes due to regional relocation and shifts in labor supply per household. As regional relocation of population tends to offset each other on the aggregate, the cross-county estimate on the impact of flood risk can overestimate the aggregate productivity effects. Finally, our model incorporates the *love of variety* channel, where the aggregate output also responds to changes in the amount of varieties. This channel matters for welfare but is not captured by the GDP data (Broda and Weinstein 2006).

5 Quantification

In this section, we calibrate our model to the US counties in 2018. We first obtain some parameters directly from the literature and our data. We then simulate the model to discipline the remaining parameters to match the targeted moments.

5.1 Exogenously Calibrated Parameters

Panel A of Table 4 shows parameter values obtained directly from the literature and the data. We treat each region as a county, and there are $M = 2,772$ counties with available data on population, GDP, and flood probability, and these counties combined accounted for 96% of US aggregate GDP in 2018. We set the elasticity of substitution across varieties $\sigma = 5$, which is the mean estimate in the trade literature (Head and Mayer 2014). We obtain annual exit rate $\bar{\kappa} = 0.08$ for the U.S. firms from the County Business Patterns data in 2018.

We adjust data on the share of areas in flood zones to be consistent with the probability of the floods used to estimate actual damages. Specifically, we regress county-year-level actual shares of flooded area between 2015–2019 on county-level shares of areas in flood zones in 2018. We use the estimated intercept and slope to translate the share of areas in flood zones into the probability of flood events $\{r_m\}$, and by our procedure, the probability $\{r_m\}$ reflects the predicted annual share of lands that experience floods. We adopt a similar procedure to use the share of areas in flood zones in 1998 to construct the probability of flood events $\{r_{m,1998}\}$ in 1998. We relegate the detailed results to Appendix C.1.

We use our reduced-form evidence to discipline the model parameters about damages of flood events $\{\delta, \delta_\kappa, \eta\}$. As the probability $\{r_m\}$ reflects the predicted annual share of lands that experience floods, our reduced-form evidence on how the increase in the share of flooded land led to GDP losses[11] and firm exits directly corresponds to the model parameters $\{\delta, \delta_k\}$. We use the evidence in Table 5 and obtain productivity damage $\delta = 0.005$ and firm exit responses $\delta_\kappa = 0.003$. Because we lack county-level amenity measures, we follow Barrage (2020) who shows that in DICE models on temperature changes, the ratio of output damages to workers' direct utility damages is around 3. Thus, we assume that $\eta = 0.002$ is roughly a third of output damages $\delta = 0.005$. We find that parameter value of η has little effect on the national-level productivity impact of floods, as it primarily affects population relocation with offsetting effects of in- and out-migration regions, as shown below.

5.2 Internally Calibrated Parameters

We calibrate four sets of region-specific parameters $\{\bar{A}_m, \bar{B}_m, f_m, \psi_m\}$ such that our model-generated moments match data on regional GDP, population, employment, and firm count. Even though all the parameters are jointly estimated, it is possible to isolate the moment that drives identification of a given moment. Specifically, GDP in each region drives identification

[11] We note that GDP data does not capture changes in the number of varieties.

of region-specific productivity $\{\bar{A}_m\}$, while given the real wages, population in each region drives identification of region-specific amenities $\{\bar{B}_m\}$. Similarly, the labor supply disutility $\{\psi_m\}$ is informed by the employment-to-population ratio in each region, and entry costs $\{f_m\}$ are informed by the amount of firms in each region. As units of GDP, population, and firm count do not affect our counterfactual results, we normalize the national total GDP, population and firm count to 1 in our baseline calibration.

Finally, we discipline the elasticities $\{\phi_M, \phi_L\}$. We apply the indirect inference approach (Gouriéroux and Monfort 1996)[12] to jointly search the elasticities $\{\phi_M, \phi_L\}$ such that our model-generated employment and population responses to changes in flood risk between 1998–2018 match actual responses.

Procedure. We jointly choose region-specific parameters $\{\bar{A}_m, \bar{B}_m, f_m, \psi_m\}$ and labor supply elasticities $\{\phi_M, \phi_L\}$ as follows. In the inner loop, given a set of $\{\phi_M, \phi_L\}$, we calibrate region-specific parameters $\{\bar{A}_m, \bar{B}_m, f_m, \psi_m\}$ such that our model matches GDP, population, firm count and the employment-to-population ratio in each region. In the outer loop, we change the probability of flood events from $\{r_m\}$ to $\{r_{m,1998}\}$. We use the model-generated data to perform the same panel regressions in Table 1 by regressing employment and population on the flood risk. We choose the labor supply elasticities $\{\phi_M, \phi_L\}$ to minimize the absolute difference between the model-generated responses and the observed coefficients.

5.3 Estimation Results

Panel B of Table 4 reports the internally calibrated parameter values. Our parameter values are reasonable. For example, the implied elasticity of regional population to real wages is $\phi_M(1 + \phi_L) \approx 2.1$, within the range of 1.1–2.5 surveyed by Fajgelbaum et al. (2018).[13]

Although the parameter values of productivity, amenity, labor disutility, and entry costs rely on the normalization and geographic levels and thus are not directly comparable across papers, Appendix Table C.1 shows that the match of our model is good: across counties, the correlation of regional GDP, population, employment-to-population ratio, and firm count between the model and the data is almost unity.

Table 5 presents the comparison of actual and model-generated regression results. Columns (1)–(2) present the targeted regression coefficients, and with the calibrated structural elastic-

[12]The indirect inference approach is a simulated method of moments procedure, where the econometrican seeks the structural parameters to minimize the distance between the estimates from econometric models on the real data and the estimates from the same econometric models estimated on the simulated data.

[13]See Table A.17 in Fajgelbaum et al. (2018).

Table 4: Parameter Values and Sources

Parameter	Value	Sources/Targeted Moments
Panel A: Exogenously Calibrated Parameters		
M—Number of counties	2,772	data
σ—Elasticity of substitution across varieties	5	Head and Mayer (2014)
$\bar{\kappa}$—Constant in firm exit rates	0.08	data
r_m—Region-specific probability of flooding	0.18 (0.10)	data
δ—GDP loss due to flooding events	0.005	see regression table
δ_k—Firm exits due to flooding events	0.003	see regression table
η—Utility loss due to flooding events	0.002	Barrage (2020)
Panel B: Internally Calibrated Parameters (Match Targeted Moments)		
$\bar{A}_m$—Region-specific productivity	2.40 (2.53)	regional real GDP
$\bar{B}_m$—Region-specific amenity	0.41 (0.66)	regional population
ψ_m—Region-specific labor supply disutility	0.35 (0.34)	regional emp-to-pop ratio
f_m—Region-specific firm entry costs	0.09 (0.03)	regional firm count
ϕ_L—Convexity of labor supply disutility	1.55	Employment and population
ϕ_M—Shape parameter of location preferences	0.83	responses to flood risks

Notes: Parameter values for $\{H_m, r_m, \bar{A}_m, \bar{B}_m, \psi_m, f_m\}$ are averages across all M counties. The standard deviations are in parentheses.

ities $\{\phi_M, \phi_L\}$, our model generates similar employment and population responses to changes in the share of areas in flood zones between 1998–2018 as in the observed data. Columns (3)–(5) present the non-targeted responses. Column (3) presents the output response to changes in flood risk, for which our model-generated estimate is smaller than the county-level data estimate but not far away from the ZIP-code-level estimates (see Table 5). Column (4) displays the responses of firm entry, and our model-generated response is close to the data estimate. In our model, the number of entrants is proportional to employment and thus, the model-generated response of firm entry mimics the employment response in Column (1). In Section 6.3.1, we discuss how changes in the model assumption on entry costs may generate different entry responses. Finally, Column (5) shows that even though higher flood risk increases the chances of firm exits conditional on firm entry, our model is able to generate the (empirically observed) negative response of the average number of firm exits to changes in flood risk because higher risk leads to fewer firms.

Table 5: Comparison of Actual and Model-generated Regression Results

	(1)	(2)	(3)	(4)	(5)
	Targeted		Non-targeted		
	Δlog(Employment)	Δlog(Population)	Δlog(Output)	Δlog(Entry)	Δlog(Exit)
Actual Data:					
flood risk	-0.171***	-0.114***	-0.337***	-0.173**	-0.119*
	(0.059)	(0.041)	(0.072)	(0.079)	(0.072)
Model-generated Data:					
flood risk	-0.176***	-0.103***	-0.182***	-0.176***	-0.174***
	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)

Note: We perform the panel regression using the observed and model-generated data in 1998 and 2018, following the same way as in even columns of Table 1.

6 Counterfactual Exercises

In this section, we apply our calibrated model to study the aggregate and distributional effects of flood risk. We also display how our quantitative results are sensitive to our parameter values and model assumptions.

6.1 Aggregate Productivity Effects of Flood Risks

Panel A of Table 6 reports the aggregate effects of flood risk in 2018, setting flood risk $\{r_m\}$ from the baseline levels to 0. We find that on the aggregate, flood risk caused a 0.52% decline in the aggregate output, as well as a 0.31% reduction in employment, a 0.30% decline in the number of firm entrants, and a 0.24% decline in the number of firm exits.

Panel B of Table 6 further decomposes the output loss into three channels—direct damages, employment, and varieties—by separately allowing population shares, labor supply and the number of varieties to respond to flood risk.[14] We further decompose employment changes into both changes in population shares (labor relocation across localities with no changes in labor supply per household in each locality), referenced as "labor relocation", and changes in labor supply per household, referenced as "labor supply".

[14]First, to separate the effects of direct damages, we simulate the effects of changes in flood risk, while keeping labor supply and population shares in each region as constant. We next allow population shares to change to single out the effects of labor relocation, and then allow labor supply to respond to further single out the effects of labor supply, while keeping the number of varieties as constant. Finally, we compute how changes in the number of varieties in each region further alter the aggregate output.

Table 6: Aggregate Effects of Flood Risk in 2018

Panel A: Aggregate Effects

	Output	Employment	Firm Entry	Firm Exits
Overall risks in 2018	-0.52%	-0.31%	-0.30%	-0.24%

Panel B: Decomposition of Output Losses

	Decomposition of Output Losses			
	Direct Damage	Labor Relocation	Labor Supply	Variety Effects
Overall risks in 2018	-0.11%	0%	-0.33%	-0.08%

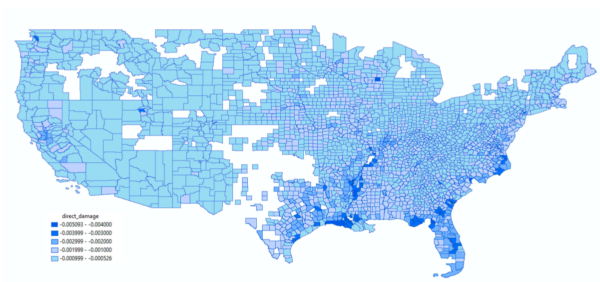
The decomposition shows that direct damages of flood risk caused a 0.11% decline in output. This magnitude is similar to the estimate by Federal Emergency Management Agency (Grimm 2020), which shows that the cost of flood damage was approximately \$17 billion annually between 2010 and 2018, representing roughly 0.1% of annual GDP. Direct damages only made up 21% of the overall output loss. In other words, ignoring adjustments of workers and firms largely underestimates the aggregate productivity loss, as illustrated by the last three columns of Panel B in Table 6. Labor relocation had little impact on aggregate output, mostly due to offsetting effects of workers' relocation across regions. The output losses due to less labor supply accounted for 63% of aggregate output losses, reflecting large amplification effects of workers' endogenous labor supply, and fewer varieties due to less firm entry accounted for another 15% of the aggregate output losses.

6.2 Distributional Effects of Flood Risk

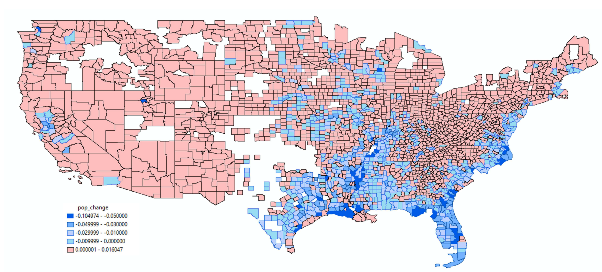
Flood risk varies greatly across locations. Whereas the output loss was 0.52% on the national level, the upper 5% and the upper 1% counties (ranked by output losses) experienced 7.9% and 13.9% loss in output, respectively. This suggests large heterogeneity in the impact of flood risk across U.S. localities.

Following the analytical result in Proposition 2, in Figure 4, we plot the county-level output changes decomposed into the main channels—direct damages, employment (population multiplied by labor supply per household), and firm entry. In terms of direct damages, we find most counties experienced negative damages, particularly those counties in the south and eastern regions (especially along the coastline), in line with the geography of flood risk shown in Figure 1. These mostly affected counties lost population to other counties, accompanied by less labor supply per household and firm entry. In line with the large drops in output, the upper 1% counties (ranked by corresponding losses in 2018) experienced a 6.1% reduction in population, a 4.7% reduction in labor supply per household, and a 10.8% loss in the amount of firms, respectively. However, for counties that were mildly affected by flood risk (e.g., some Middle Western counties), these counties were in fact "winners" from the flood risk. They benefited from labor relocation from risky coastal areas and thus enjoyed more firm entry and labor supply per worker (as more varieties increased workers' utility).

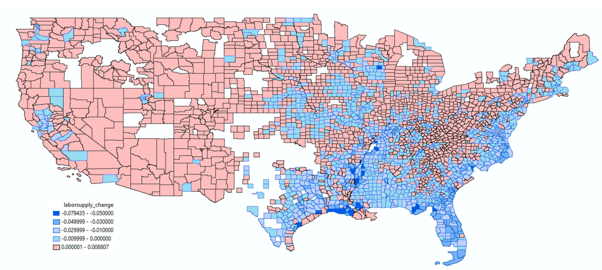
Figure 4: Distributional Effects of Flood Risks in 2018



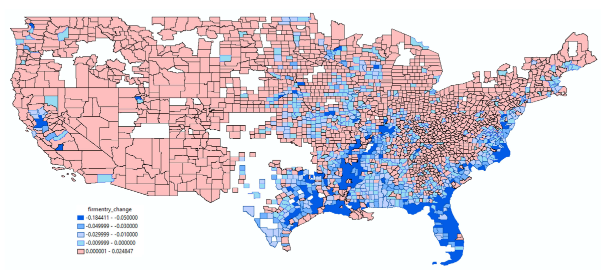
(a) Direct damages



(b) Population



(c) Labor Supply Per Worker



(d) Firm Entry

6.3 Model Extensions

6.3.1 Alternative Assumptions about Firm Entry

In our baseline model, because entry costs are paid in terms of a fixed amount of labor, changes in firm entry mimic changes in employment. We now experiment with an alternative assumption on firm entry costs. Following the recent literature showing that creating new firms also requires material costs (Atkeson and Burstein 2010, Acemoglu and Cao 2015), we consider entry costs as $f_m W_m(s)^{1-\alpha} P_m(s)^{\alpha}$, where α is the fraction of entry costs spent on final goods. Figure 5 illustrates the aggregate impact of flood risk in 2018 under different parameter values of α. The responses of firm entry to changes in flood risk increased with the share of entry costs spent on final goods, as final-good prices were more responsive to flood risk compared with wages (final-good prices were affected not only by wages, but also by firm productivity and the amount of varieties). As a result of fewer firms, the output losses of the flood risk also slightly increased with the share of entry costs spent on final goods. As shown in Table 7, when entry costs were fully paid by final goods ($\alpha = 1$), the aggregate output loss of the flood risk was -0.57%, larger than the baseline result -0.52%.

Figure 5: Entry Costs and Aggregate Impact of Flood Risks

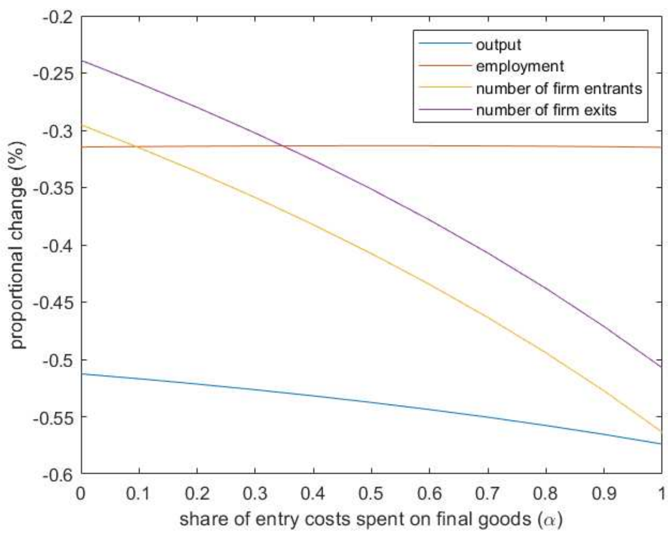


Table 7: The Aggregate Impact of Flood Risks in 2018 under Different Model Extensions

	Output	Employment	Firm Entry	Firm Exits
(1) Baseline model	-0.52%	-0.31%	-0.30%	-0.24%
(2) Entry costs paid in goods	-0.57%	-0.31%	-0.56%	-0.51%
(3) Allowing for interregional trade	-0.62%	-0.47%	-0.41%	-0.35%
(4) Allowing for capital & intermediate inputs	-0.67%	-0.38%	-0.36%	-0.31%

6.3.2 Interregional Trade Networks

In the baseline model, we abstract from good flows across regions. In Appendix B.4, we extend the model to consider two sectors—traded and nontraded sectors—in each county. In the environment with cross-regional trade flows, workers' real wages tend to be less responsive to changes in local flood risk than in the autarkic economies. One reason is that in contrast with the baseline model, workers' demand is diversified across locations in the traded sector and thus are less affected by changes in the prices of local traded goods. Thus, we find that in the recalibration, we require a larger value of labor supply elasticity ($\phi_L = 1.72$) to match the observed employment changes in response to changes in local flood risk. As a result of a larger labor supply elasticity, the aggregate output loss due to overall flood risk was 0.62% in 2018, slightly larger than 0.52% in our baseline model.

6.3.3 Capital and Land

Our baseline model assumes labor to be the only input in the firm production. In Appendix B.5, we extend the model to consider both capital and land in the firm production. Capital is mobile across regions and can be rented at a constant real rate from the global market, whereas land is supplied at a fixed amount and thus generates the congestion force in the regional production. We recalibrate the model to the data. As shown in Table 7, in this alternative model, the output losses due to flood risk were 0.67% in 2018, larger than 0.52% in our baseline model. The main reason is that flood risk not only lowered employment, but also lowered the capital-to-labor ratio,[15] as capital usage became relatively more expensive relative to labor in the presence of the flood risk.[16] This force outweighs the congestion effect caused by land, as the land share in production is small (Caselli and Coleman 2001).

All together, these extensions imply a larger impacts of flood risk on the economy when we allow for more forces. Meanwhile, they reveal the quantitative importance of the economic forces in our simplified baseline model.

6.4 Future Changes in Flood Risk

Flood risk is likely to increase as a result of greenhouse gas emissions. To gauge how such future changes in flood risk affect the US economy, we use the First Street Foundation's county-level predictions on proportional changes in flood risk between 2020–2050 to adjust the flood risk $\{r_m\}$ in our baseline model. On average, the share of properties with flood risk increases by 4.5% between 2020 and 2050.

[15] Quantitatively, flood risk in 2018 lowered the US aggregate capital-to-labor ratio by 0.34%.

[16] The real return of capital remained constant, whereas in the presence of the flood risk, workers' real wages declined.

Table 8: Aggregate Effects of Future Changes in Flood Risks, 2020–2050

Panel A: Aggregate Effects				
	Output	Employment	Firm Entry	Firm Exits
Changes in risks, 2020–2050	-0.12%	-0.05%	-0.05%	-0.04%
Panel B: Decomposition of Output Losses				
	Decomposition of Output Losses			
	Direct Damage	Labor Relocation	Labor Supply	Variety Effects
Changes in risks, 2020–2050	-0.014%	0%	-0.086%	-0.024%

Table 8 shows that the predicted increase in flood risk between 2020–2050 will cause a 0.12% decline in aggregate output, of which the magnitude is comparable to Desmet et al. (2021) who show that sea level rises due to climate changes will lead to a 0.11% loss in global real GDP in 2200. As before, we find that only 12% of the output losses arise from direct damages.[17] The rest of output losses come from reduced labor supply and firm entry, suggesting the importance of incorporating long-run adjustments of workers and firms.

7 Conclusion

Using recently available data, we demonstrate that increased flood risk has large negative impacts on firm entry, employment and output in the long run, whereas flood events reduce output in the short run. Motivated by these findings, we develop and quantify a spatial equilibrium model to estimate the aggregate impact of increasing flood risk. In our model, expecting flood risk, firms choose whether to enter a locality, while workers choose whether to relocate and how much labor to supply. For a given locality, realized floods affect firms' average productivity and worker's average amenity. Quantitatively, we find that flood risk reduced U.S. aggregate output by 0.52% in 2018, 80% of which stemmed from expectation of floods and 20% from direct damages.

Our results highlight that only accounting for direct damages largely underestimates the

[17]Here the role of direct damages in output losses is smaller than what we found in Table 6 for the effect of the flood risk in 2018. This is because compared with the flood risk in 2018, the predicted increase in the flood risk is more positively correlated with regional productivity levels. In our model, higher risk in more productive regions would result in larger aggregate amplification effects (for example, more people would leave highly productive regions, which in turn lowers firm entry and affects labor supply in these regions).

actual losses of natural disasters, as firms and workers will rationally change their economic activities in expectation of risk of these natural disasters. Thus, any policy aiming to alleviate the climate damages needs to take into account firms' and workers' long-run adjustments.

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A Reduced-form Evidence: Additional Results

Table A.1: Summary Statistics

Panel A: Outcome Variables

	(1) log(Entry)	(2) log(Exit)	(3) log(Employment)	(4) log(Population)	(5) log(Real GDP)[a]
Year = 1998	4.07	3.96	8.79	9.72	13.47
	(1.46)	(1.42)	(1.75)	(1.33)	(1.60)
Year = 2018	3.83	3.82	8.89	9.80	13.79
	(1.53)	(1.48)	(1.78)	(1.53)	(1.61)

Panel B: Demographic and Economic Controls

	(1) Manufa. share	(2) Female share	(3) ΔChina import	(4) Pop per sqkm	(5) Cum. flood share
Year = 1998	0.21	0.51		40	0.31
	(0.15)	(0.02)		(160)	(0.44)
Year = 2018	0.16	0.50	25.92	60	5.04
	(0.13)	(0.02)	(10.78)	(300)	(3.13)

Panel C: Independent Variables

	(1) Flood risk	(2) Flood share
Year = Initial_Year[b]	0.06	0.07
	(0.13)	(0.23)
Year = 2018	0.12	0.23
	(0.14)	(0.40)

Notes: a,b: The initial year is 2001 instead of 1998 for the short run regressions using actual flood share as the key independent variable, since the BEA county-level GDP data starts from 2001. Sources: Autor et al. (2013), Bureau of Economic Analysis and US Census data series. The standard deviations are in parentheses.

Table A.2: The Impact of Long Run Change in Flood Risk: Fixed Effects Estimates, Q3

	(1)	(2)	(3)	(4)	(5)
	log(Entry)	log(Exit)	log(Employment)	log(Population)	log(Output)
Flood risk	-0.357**	-0.217	-0.333***	-0.240**	-0.226*
	(0.150)	(0.159)	(0.115)	(0.104)	(0.130)
Observations	2304	2298	2326	2326	2300
County FE	Yes	Yes	Yes	Yes	Yes
State×Year	Yes	Yes	Yes	Yes	Yes
Other Controls	Yes	Yes	Yes	Yes	Yes
Flood Cumulative	Yes	Yes	Yes	Yes	Yes

Notes: The sample is limited to counties where Q3 maps are available in 1998. Outcome variables are changes in log terms. The main independent variable $D.FloodRisk_{i,t}$ represents changes in the percentage of land area within FEMA's special flood zone in locality i between years 1998 and 2018. "IV" represents our instrumental variable approach, using the interaction of average changes in flood risk in the rest of the state and a county's own geo-climatic features as instruments. All regressions control for state fixed effects, cumulative flood area and a rich set of demographic and economic controls. Standard errors are clustered at the county level.

Table A.3: The Impact of Long Run Change in Flood Risk: Change-on-Change Estimates, Placebo

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Δlog(Entry)		Δlog(Exit)		Δlog(Employment)		Δlog(Population)	
ΔFlood risk	0.001	0.088	0.063	0.072	-0.049	-0.026	0.079*	0.031
	(0.060)	(0.120)	(0.063)	(0.147)	(0.039)	(0.111)	(0.043)	(0.151)
Observations	2607	1154	2613	1155	2643	1163	2644	1163
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Flood Cumulative	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample		Q3		Q3		Q3		Q3

Notes: The sample uses placebo outcome data in 1990 and 1998. Outcome variables are changes in log terms. The main independent variable $D.FloodRisk_{i,t}$ represents changes in the percentage of land area within FEMA's special flood zone in locality i between years 1998 and 2018. "IV" represents our instrumental variable approach, using the interaction of average changes in flood risk in the rest of the state and a county's own geo-climatic features as instruments. All regressions control for state fixed effects, cumulative flood area and a rich set of demographic and economic controls. Standard errors are clustered at the county level.

Table A.4: The Impact of Short Run Actual Floods: Fixed Effects Estimates, Lagged Shocks

	(1)	(2)	(3)	(4)	(5)
	log(Entry)	log(Exit)	log(Employment)	log(Population)	log(Output)
Flood share	0.000	0.003	-0.001	0.001***	-0.005***
	(0.004)	(0.004)	(0.001)	(0.000)	(0.002)
L.Flood share	-0.004	0.004	-0.000	0.000	-0.000
	(0.004)	(0.004)	(0.001)	(0.000)	(0.002)
Observations	50782	50931	52666	52683	51816
County FE	Yes	Yes	Yes	Yes	Yes
State×Year FE	Yes	Yes	Yes	Yes	Yes
Initial Controls Trends	Yes	Yes	Yes	Yes	Yes
ymean	4.036	3.991	8.870	9.825	13.67

Notes: Outcome variables are changes in log terms. The main independent variable $Floodshare_{i,t}$ represents changes in the percentage of land area flooded in county i, year t. We are interested in the short run impact of yearly floods and the sample period is 2001-2018. All regressions control for county fixed effects, state-by-year fixed effects, and a rich set of initial controls by year trends. Standard errors are clustered at the county level.

B Proofs

B.1 Labor Supply and Location Choices

We first obtain the optimal labor supply l_m for households that stay in m. Households' utility can be written as:

$$\sum_s \Pr(s)U_m(s) = \sum_s \Pr(s)v_m B_m(s)\left[\frac{W_m(s)}{P_m(s)}l_m - \psi_m \frac{l_m^{1+1/\phi_L}}{1+1/\phi_L}\right]. \tag{B.1}$$

Taking the first-order condition with regard to labor supply l_m, we obtain:

$$\sum_s \Pr(s)v_m B_m(s)\frac{W_m(s)}{P_m(s)} = \sum_s \Pr(s)v_m B_m(s)\psi_m l_m^{1/\phi_L}. \tag{B.2}$$

After some arrangement of the equation, we can obtain labor supply in equation (9). By plugging equation (B.2) into equation (B.1), we obtain:

$$\sum_s \Pr(s)U_m(s) = \sum_s \Pr(s)v_m B_m(s)\psi_m \frac{l_m^{1+1/\phi_L}/\phi_L}{1+1/\phi_L}. \tag{B.3}$$

For ease of notation, denote $x_m = \sum_s \Pr(s)B_m(s)\psi_m \frac{l_m^{1+1/\phi_L}/\phi_L}{1+1/\phi_L}$. Thus, a worker would choose location m if $v_m x_m \geq v_n x_n \;\forall\, n$. Note that location preference v_m follows Fréchet distribution $G_m(v_m) = \exp(-v_m^{-\phi_M})$ and is i.i.d. across locations. Therefore,

$$\begin{aligned}
\Lambda_m &= \int_0^\infty \prod_{n\neq m} G_n\left(\frac{v_m x_m}{x_n}\right) g_m(v_m)dv_m \\
&= \int_0^\infty \exp\left(-\sum_n \left(\frac{x_m}{x_n}\right)^{-\phi_M} v_m^{-\phi_M}\right)\phi_M v_m^{-\phi_M-1}dv_m \\
&= \frac{x_m^{\phi_M}}{\sum_n x_n^{\phi_M}}.
\end{aligned} \tag{B.4}$$

The first equality defines the probability of choosing location m, which is a weighted average of the probability to choose location m under location preference v_m, $\prod_{n\neq m} G_n\left(\frac{v_m x_m}{x_n}\right)$,[18] over the distribution of location preference v_m. The second equality uses the cumulative and

[18] Under location preference v_m, the probability of v_n such that $v_m x_m \geq v_n x_n$ is $G_n\left(\frac{v_m x_m}{x_n}\right)$.

density probability of G_m. The third equality computes the integral of the equation. After plugging $x_m = \sum_s \Pr(s) B_m(s) \psi_m \frac{l_m^{1+1/\phi_L}/\phi_L}{1+1/\phi_L}$ into the equation, we obtain equation (10).

B.2 Proof of Proposition 1

Note from equation (9), $L_m \propto \Lambda_m l_m$, and $N_m(s) \propto L_m(1-\kappa(s))$, we can solve l_m as a function of Λ_m up to a constant.

$$l_m \propto (\Lambda_m)^{\frac{\frac{\phi_L}{\sigma-1}}{1-\frac{\phi_L}{\sigma-1}}} \tag{B.5}$$

Plugging l_m into equation (10), we obtain:

$$\Lambda_m = \frac{C_m (\Lambda_m)^{\frac{\phi_M(1+\phi_L)}{\sigma-1-\phi_L}}}{\sum_{m'} C_{m'} (\Lambda_{m'})^{\frac{\phi_M(1+\phi_L)}{\sigma-1-\phi_L}}} \tag{B.6}$$

where C_m is a region-specific constant and also captures damages of floods. For ease of notation, let $\delta = \frac{\phi_M(1+\phi_L)}{\sigma-1-\phi_L}$.

We are interested in whether equation (B.6) yields a unique solution of $\{\Lambda_m\}$. To make progress, define $x_{m,1} = \Lambda_m$ and $x_{m,2} = \sum_{m'} C_{m'} (\Lambda_{m'})^{\delta}$. Then equation (B.6) can be reformulated by a system of equations:

$$x_{m,1} = C_m x_{m,1}^{\delta} x_{m,2}^{-1}, \tag{B.7}$$

$$x_{m,2} = \sum_{m'} C_{m'} x_{m',1}^{\delta}. \tag{B.8}$$

Then we can apply Theorem 1 in Allen et al. (2015) to show the unique of the equilibrium. Specifically, define:

$$\Gamma = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$

$$B = \begin{bmatrix} \delta & -1 \\ 0 & \delta \end{bmatrix}$$

Theorem 1 in Allen et al. (2015) shows that if the largest eigenvalue of $|B\Gamma^{-1}|$ is smaller or equal to 1, which means that $|\delta| \leq 1$, there is at most one strictly positive solution. After solving $\{\Lambda_m\}$, all other variables are uniquely pinned down. In particular, l_m is uniquely determined by equation (B.5), and aggregate output is determined by equation (13).

B.3 Proof of Proposition 2

We first log-linear equation (15) and take the full derivative.

$$d\hat{\Lambda}_m = \phi_M \left[(1 + 1/\phi_L)d\hat{l}_m - \eta dr_m\right] \tag{B.9}$$

Thus, we obtain equation (17). Noting that $L_m \propto \Lambda_m l_m$ and $N_m(s) \propto L_m(1 - \kappa(s))$, we can also easily obtain $d\hat{L}_m = d\hat{\Lambda}_m + d\hat{l}_m$ and $d\widehat{\mathbb{E}N}_m = d\hat{L}_m - \bar{\kappa}\delta_\kappa dr_m$ as in equations (18)–(19). We then log-linear equation (14) and take the full derivative around $r_m = 0$:

$$\begin{aligned} d\hat{l}_m &= -\phi_L \left(\delta + \frac{1}{\sigma - 1}\bar{\kappa}\delta_\kappa\right) dr_m + \frac{\phi_L}{\sigma - 1} d\hat{N}_m \\ &= -\phi_L \left(\delta + \frac{1}{\sigma - 1}\bar{\kappa}\delta_\kappa\right) dr_m + \frac{\phi_L}{\sigma - 1}\left(d\hat{\Lambda}_m + d\hat{l}_m\right) \\ &= -\phi_L \left(\delta + \frac{1}{\sigma - 1}\bar{\kappa}\delta_\kappa\right) dr_m + \frac{\phi_L}{\sigma - 1}\Big(\left(\phi_M(1 + 1/\phi_L) + 1\right) d\hat{l}_m - \phi_M \eta dr_m\Big). \end{aligned} \tag{B.10}$$

The first equality is the result of log-linearization and full derivation. The second equality uses $d\hat{N}_m = d\hat{L}_m$ and $d\hat{L}_m = d\hat{\Lambda}_m + d\hat{l}_m$. The third equality uses $d\hat{\Lambda}_m = \phi_M \left[(1 + 1/\phi_L)d\hat{l}_m - \eta dr_m\right]$. Noting that there is only one unknown $d\hat{l}_m$ in equation B.10, we can solve $d\hat{l}_m$ as an equation of dr_m in equation (16).

Finally, from equation (13) and the damage equation of flooding, we obtain the average output:

$$\mathbb{E}Y_m \propto \sum_s \Pr(s) A_m(s) N_m(s)^{\frac{1}{\sigma-1}} L_m. \tag{B.11}$$

Taking the log-linearization and full derivation around $r_m = 0$, we obtain:

$$d\widehat{\mathbb{E}Y}_m = -\delta dr_m + d\hat{L}_m + \frac{1}{\sigma - 1} d\widehat{\mathbb{E}N}_m. \tag{B.12}$$

Therefore, we obtain equation (20).

B.4 Two-sector Model

We now extend the model to consider two sectors—traded and non-traded sectors $j \in \{T, NT\}$. For each sector in region m, there is a composite good composed of differentiated varieties (firms) sourced from different origins, according to the CES technology,

$$Y_m^j(s) = \left(\sum_n \int_{\Omega_{nm}^j(s)} y(v,s)^{\frac{\sigma-1}{\sigma}} dv \right)^{\frac{\sigma}{\sigma-1}} \tag{B.13}$$

where $\Omega_{nm}^j(s)$ is the set of firms that trade from origin n in state s. For the nontradable sector that does not source from other regions, $\Omega_{nm}^{NT}(s) = \emptyset \ \forall \ n \neq m$. For the traded sector, the iceberg trade costs from n to m are assumed to be $\tau_{nm} = (dist_{nm})^{\gamma} \geq 1 \ \forall n \neq m$ and $\tau_{nm} = 1 \ \forall n = m$, where γ is the elastcity of trade costs with regard to physical distance, and there are no fixed marketing costs (Krugman 1980). The free-entry conditions of firms in both sectors are identical as in Section 6.3.1. Workers in each region consume traded and non-traded goods with expenditure shares β and $(1-\beta)$ respectively.

We calibrate $\beta = 0.3$ to match the share of employment in the non-traded sector from the Population Census in 2000.[19] We calibrate γ to match the elasticity of good flows with regard to distance estimated from the Commodity Flow Survey (Allen and Arkolakis 2014).[20] We recalibrate all internally calibrated parameters following the procedure in Section 5.2.

B.5 Capital and Land

We now extend the production function in region m to allow for capital and land:

$$y_m(s) = A_m(s) \left[(l_m^d(s))^{\beta} (k_m^d(s))^{1-\beta} \right]^{1-\theta} h_m^d(s)^{\theta} \tag{B.14}$$

where θ is the share of costs spent on land. The parameters $\beta(1-\theta)$ and $(1-\beta)(1-\theta)$ are the cost shares of labor and capital in the production, respectively.

We consider that capital can be rented at the real return R from the global market, whereas land is supplied at a fixed amount H_m in each region. To close the model, we assume that both capital income and labor income are spent on final goods in the local area. In the recalibration, we obtain the land share in the US production $\theta = 0.06$ from Caselli and Coleman (2001) and the region-specific land area $\{H_m\}$ directly from the data. We consider $\beta = 2/3$ such that the labor share in the total income is roughly two thirds. We set $R = 0.08$ according to the real internal rate of return in the US from the Penn World Table.

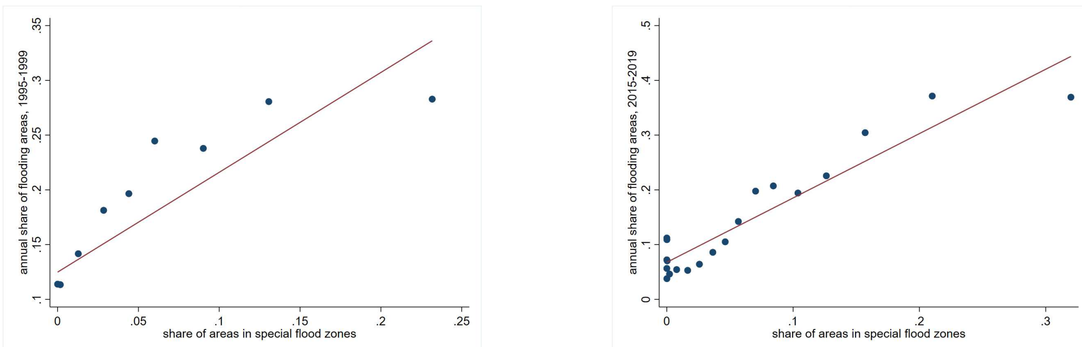
[19] Following Fajgelbaum (2020), the following sectors are included in the non-traded sector: construction, retailer, hotels and restaurants, real estate, education, health and social work.

[20] In the traded sector, the elasticity of trade flows with regard to distance is $(\sigma-1)\gamma$.

C Quantitative Analyses: Additional Results

C.1 Special Flood Zones and Actual Flood Risks

Figure C.1: Relationship between Annual Share of Flooding Areas and Share of Special Flood Zones, across Counties



(a) Relationship in 1998 **(b)** Relationship in 2018

Note: We group counties into 20 bins (fewer with fewer discrete numbers) ranked by the share of properties in flood zones.

Table C.1: Targeted Moments in the Data and Model

Targeted Moments	Data	Model	Corr.
Regional real GDP (national total normalized to 1)	4e-4 (2e-3)	4e-4 (2e-3)	1.00
Regional population (national total normalized to 1)	4e-4 (1e-3)	4e-4 (1e-3)	1.00
Regional employment-to-population ratio	0.45 (0.20)	0.45 (0.20)	1.00
Regional firm count (national total normalized to 1)	4e-4 (1e-3)	4e-4 (1e-3)	1.00

Notes: For each moment, we present the averages across all M counties using the actual data and the model-generated data. The standard deviations are in parentheses. The last column presents the cross-county correlation between actual moments and model-generated moments.