Expecting Floods: Firm Entry, Employment, and Aggregate Implications*

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Abstract

Using county-level and ZIP-code-level data from the United States during 1998–2018, we document: (1) increased flood risk has a large negative impact on firm entry, employment, and output in the long run; and (2) flood events reduce output in the short run while their impact on firm entry and employment is limited. We then develop a quantitative spatial model to characterize how flood risk shapes firms' location choices and workers' employment. We find that flood risk reduced U.S. aggregate output by 0.52% in 2018, 20% of which stemmed from direct damages and 80% from long-run adjustments of firms and workers.

JEL Codes: C21; F18; Q54; R12

Key Words: flood risk; spatial equilibrium; long-run adjustments of workers and firms

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1 Introduction

Floods are the most frequent natural disasters in many countries. In recent decades, flood events have become increasingly common, and the risk of floods has risen due to the intensifying water cycles and sea level rise associated with climate change. For example, the Federal Emergency Management Agency (FEMA) reported that in 2018, about 13 million Americans resided within a 100-year flood zone in the U.S. As global warming persists, the floodplains in the U.S. are projected to expand by approximately 45% by the end of this century (AECOM, 2013). In this paper, we explore the effects of increasing flood risk on the economy by examining the responses of firms and workers. Utilizing data from the U.S., we study how flood risk and flood events influence firms' location decisions and workers' employment. Additionally, we quantify the impact of flood risk on aggregate output.

While there is existing literature on the economic impact of floods, the majority of studies have concentrated on actual flood events, and some recent research examines the effect of flood risk on housing prices (e.g., Hino and Burke, 2020). However, there are few studies exploring how increasing flood risk influences firm entry and employment, partly due to the absence of suitable data. In this paper, we address this gap by employing digitized national flood risk data over an extended period and linking it with county-level and ZIP-code-level information on firms' entry, employment, and other outcomes between 1998 and 2018.

Using a panel data regression design that controls for county fixed effects, year fixed effects, and various confounding factors, we present two primary empirical findings. First, increased flood risk has a substantial negative impact on firm entry, employment, and output in the long run. Specifically, a one-standard-deviation increase in flood risk during the two-decade study period reduces firm entry by 1.7%, employment by 2.0%, and real GDP by 2.8%. Although the impact on population size is also negative, its magnitude (1.3%) is smaller than that on employment. Moreover, firm exits decrease with increased flood risk, indicating reduced business dynamism in a hazardous environment. Second, in contrast to the long-run effects of increased flood risk, yearly flood events have a limited impact on firm entry and employment in the short run but diminish real GDP, consistent with the fact that actual floods affect the productivity of existing firms. Specifically, a one-standard-deviation increase in the share of flooded areas reduces real GDP in the same year by 0.2%.

A crucial empirical challenge is that the flood risk updates using FEMA maps may be subject to endogeneity concerns and measurement errors. Some of the data used in FEMA modeling are outdated or inaccurate (Kousky, 2018). Additionally, since these FEMA maps are used to rate national flood insurance policies, FEMA map updates are influenced by map revision requests or other economic considerations (Flavelle et al., 2020). For our analysis, we assume that these risk measures are what firms and workers have observed and, therefore, affect their decisions. To address the potential measurement and identification concerns, we conduct three robustness checks. First, we employ a cross-fit partialing-out LASSO-IV approach to select the best predictors of flood risk changes, choosing among geo-climatic variables, the average changes in flood risk in the rest of the state, and their interactions. We demonstrate that our LASSO-IV estimates are comparable in magnitude to those obtained from the fixed effect model. Second, our findings remain robust when using ZIP-code-level data that exploit finer spatial variations. Finally, we construct an alternative measure of flood risk updates using scientific model-based data from First Street Foundation, which is less affected by political pressures, insurance concerns, and other local economic considerations. Using this alternative measure of flood risk, we obtain similar regression results.

Motivated by our reduced-form findings, we develop a spatial equilibrium model featuring firm entry (Krugman, 1980) and workers' location choices (McFadden, 1978) to reveal the aggregate impact of flood risk. In our model, firms and workers make long-run adjustments in anticipation of flood risk: firms decide whether to enter a locality to produce and serve local consumers, while workers determine their labor supply and consider relocation. Realized floods have short-run effects by influencing firms' average productivity and workers' average amenities for a given locality. The equilibrium wage connects the decisions of firms and workers. Our model highlights three channels through which flood risk affects the economy. 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 lower real wages. The third is a *love-of-variety* channel, illustrated by the declining number of firms as flood risk increases.

We calibrate our model by targeting the responses of employment and population to flood risk through indirect inference. For the non-targeted moments (output, firm entry, and firm exit), our model-generated responses to flood risk align with those based on micro data. This consistency indicates that our model captures essential forces in the economy.

Using 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 in 2018, flood risk caused a 0.53% decline in aggregate output, of which 0.12% was due to the direct damage channel, 0.33% was due to the employment channel, and 0.08% was due to the variety channel. The latter two have not been much studied by the literature on natural disasters. Second, we study the distributional impact across regions. The average decline masks wide regional variation, as the loss of output in the top 5% counties in the flood risk distribution (in areas such as Cape May in New Jersey) was as high as 9–16% of county-level output. Third, we apply our model to a future scenario in which the share of properties with flood risk increases by 4.5% between 2020 and 2050 (First-Street-Foundation, 2018) and find that this increase would cause a 0.13% decline in aggregate output. Once again, underlying this impact, the reduced employment in long-run adjustments of floods plays a more crucial role than direct damages, a finding that has not been emphasized by the existing literature.

Finally, we examine various extensions of our model, such as assuming that establishing a new firm necessitates a combination of labor and final goods, incorporating cross-regional trade flows, considering both land and capital in firm production, and allowing for firm productivity heterogeneity (Melitz, 2003). Most of these extensions anticipate a marginally greater impact of flood risk on the economy, and the relatively small differences in magnitudes underscore the quantitative significance of the economic forces within our parsimonious baseline model.

Our study contributes to the growing literature on the quantitative effects of climate change on spatial economies (e.g., Costinot, Donaldson and Smith, 2016; Alvarez and Rossi-Hansberg, 2021; Castro-Vincenzi, 2023).[1] Bilal and Rossi-Hansberg (2023) and Rudik et al. (2022) incorporate forward-looking migration in dynamic spatial equilibrium models to assess the impacts of extreme temperature and storms. Leduc and Wilson (2023) offer estimates on the long run adjustments to extreme temperatures in the US using a panel distributed lag approach. Our study is particularly related to two previous 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 investment in local technology. Balboni (2019) study the misallocation of infrastructure in the presence of coastal flooding driven by the risk of sea-level changes. While the previous literature has primarily focused on coastal flooding

[1]There is also a large body of literature that develops macro models to evaluate the impact of climate change on the national level (e.g., Acemoglu et al., 2012; Golosov et al., 2014; Barrage, 2020; Rudik, 2020; Fried, 2021; Nath, 2022).

due to sea-level rise, we leverage a new data source (historic and recent maps of flood zone designation). This allows our empirical and quantitative analysis to incorporate overall flood risk, and we investigate the production damage of floods rather than reduced land supply due to coastal sea level rise. Second, we reconcile the quantitative analysis with our reduced-form evidence, which highlights that firms' (and workers') responses to flood risk differ from their responses to actual floods. Another relevant study by Lin, McDermott and Michaels (2021) finds increasing residential housing construction due to urban agglomerations within a 10km radius of the US Atlantic and Gulf coasts, areas that were already prone to flooding during the 20th century. Our research complements this study by focusing on national changes in flood risk and specifically explores the productivity damage caused by the increase in flood risk, utilizing firm, output, and employment data.

Our micro-level evidence is based on spatially granular panel data on flood risk. Existing research on flood risk focuses on housing price effects. For example, using the same historic flood risk data as ours, Hino and Burke (2020) demonstrate that increased flood risk reduces property values by 1–2%. Wagner (2022) uses recent flood designation map and flood insurance data to study optimal policy in the natural disaster insurance market. 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 explicitly model housing, the housing price effect can be interpreted as a change in amenity in our model.[2]

Our study is also related to a growing empirical literature on the economic consequences of natural disasters, particularly those closely related to economic growth (e.g., Bansal and Ochoa, 2011; Dell, Jones and Olken, 2012), as reviewed by Dell, Jones and Olken (2014).[3] Our work is particularly related to Kocornik-Mina et al. (2020), which uses satellite nightlight data to evaluate the impact of large-scale floods across global cities. Our findings on flood events are consistent with theirs: flood events reduce output, but their impact does not last

[2]Our estimate is also comparable to theirs. Since housing prices can be interpreted as the present value 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 risk reduces workers' utility by 0.3–0.6% through housing damage, which is similar to our calibrated amenity loss of 0.2%.

[3]Recent studies include Gallagher (2014), Hsiang and Jina (2014), Burke, Hsiang and Miguel (2015), Deryugina (2017), Hsiang et al. (2017), Bakkensen and Barrage (2018), Tran and Wilson (2021), and Nath, Ramey and Klenow (2023), among others.

long, suggesting a fast recovery. In contrast, we demonstrate that flood risk can have long-run consequences, and the long-run impact can be more severe than the short-run impact, as it changes firms' and workers' behavior. In addition to providing reduced-form evidence, our study *quantifies* the importance of considering both long-run adjustment effects and direct damages in assessing the aggregate consequences of natural disasters.

This paper is structured as follows. Section 2 presents our data and measurement, while Section 3 provides the reduced-form evidence that leads to the model developed in Section 4. Section 5 applies the model to the data, and Section 6 presents counterfactual exercises to reveal the aggregate and distributional effects of flood risk. Section 7 concludes.

2 Data

Flood Risk. We use two major sources of data on flood risk. Our first source is FEMA's historical and current designation maps of Special Flood Hazard Zones. The maps for historical flood zone designations, Q3, correspond to FEMA's Flood Insurance Rate Map in 1998. These maps assign flood zone designations at the polygon level and are used to determine national flood insurance premiums. The Special Flood Hazard Zones identified from these maps represent areas that have at least a 1% probability of being inundated by a flood event in any given year. In our analysis, we consider areas in Special Flood Hazard Zones as the FEMA floodplain (areas with flood risk). Since FEMA's map modernization process in the early 2000s, there have been numerous revisions to FEMA's flood risk designations, based on new flood data and updated modeling methods. To take advantage of these changes, we also obtain the current floodplain designation maps from FEMA's National Flood Hazard Layer (NFHL), which are for the year 2018.[4]

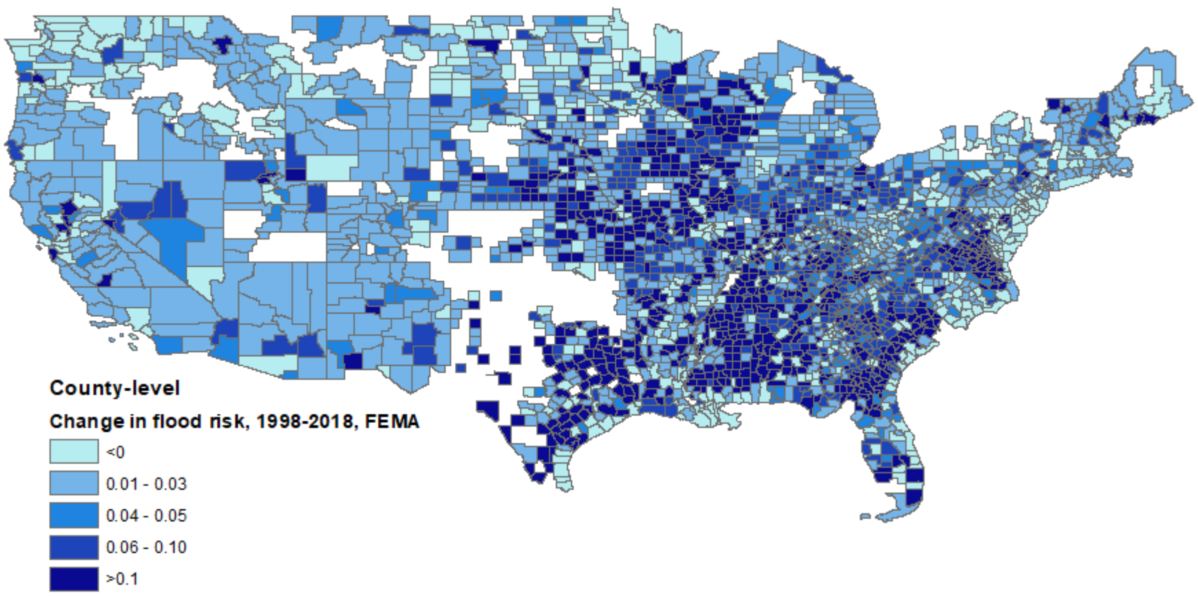
We use map layers of FEMA's flood zone designations in 1998 or 2018 to calculate the proportion of land areas in FEMA's flood zones for each county-level and ZIP-code-level tabulation area in either 1998 or 2018.[5] For our baseline analysis, We use the proportion of areas within flood zones as the measure of flood risk. Many counties experienced a significant increase in flood risk during our sample period. In Figure 1, we plot the change in flood risk

[4]FEMA determines flood risk designation based on factors such as building construction, geography, precipitation patterns, etc.

[5]To minimize measurement errors, we exclude outliers in our analysis.

from 1998 to 2018 at the county level. The figure shows that many counties experienced a significant increase in flood risk during our sample period. On average, the proportion of land areas in flood zones increased by 6 percentage points, with a 19-percentage-point increase in the 90th percentile across the distribution of county-level flood risk changes.

Figure 1: Change in Flood Risk, County-Level, 1998-2018



Notes: Flood risk at the county level is measured by the share of land areas within the 100-year floodplain. The map illustrates the changes in the proportion of land within the 100-year floodplain between 1998 and 2018 for each county. Blank areas on the map indicate regions without flood map coverage based on FEMA maps accessed in 2018.

A significant challenge in using FEMA maps to construct measures of flood risk updates, as stated in the introduction, involves potential endogeneity concerns and measurement errors (Pralle, 2019).[6] To tackle these identification challenges and enhance the confidence in the robustness of our empirical results, we will take a LASSO-IV approach below to select geo-climatic conditions that best predict changes in flood risk. This approach allows for nonlinear interactions between geo-climatic variables while reducing researchers' discretion in the first-stage selection process.

Another approach we take to address the endogeneity of FEMA map revisions is to construct an alternative measure of flood risk update. We utilize a second data source for

[6]For example, since FEMA's map modernization process in the early 2000s, FEMA map revisions are influenced by Letter of Map Amendment (LOMA) and Letter of Map Revision (LOMR) requests from individuals and and communities.

flood risk updates in 2018, based on scientifically derived flood-model predictions from First Street Foundation. The publicly available, county-level flood risk data from First Street Foundation provides the percentage of properties within the 100-year floodplain in 2018. We use FEMA Q3 and satellite data from the Global Human Settlement Layers (GHSL) to construct the corresponding measure in 1998. In Figure A.2, we plot the change in flood risk from 1998 to 2018 at the county level, measured as the change in the percentage of properties within the 100-year floodplain in 2018. The flood risk variations constructed using the historic FEMA map in 1998 and the recent layer from First Street Foundation in 2018 reflect substantial flood risk increases in both inland and coastal counties.

First Street Foundation does not have a historic flood risk map for 1998. In 1998, FEMA flood zone designation is the primary sources of flood risk information for firms and households, since more accurate and scientific flood risk maps are rare at the time. For the purpose of our analysis, flood risk perception is the primary factor affecting firms' and households' decision making process. For these reasons, we use FEMA maps in 1998 as the historic flood map providing flood risk information in 1998.

Flood Events. Consistent with the prior literature (e.g., Kocornik-Mina et al., 2020), we obtained our spatial data on actual floods from the Dartmouth Flood Observatory (DFO). These data document the frequency and intensity of flood events worldwide and have been accessible from 1985 to the present.

Firm and Labor Outcomes. Our study focuses on how both firms and workers respond to the events under investigation. To this end, we obtained the county-level numbers of establishment entrants and exits for each year of interest from the U.S. Census's Business Dynamics Statistics. In our empirical and quantitative analyses, we treat each establishment as a firm due to its status as the fundamental production unit in the available data.[7] On the worker side, we acquired employment data from the U.S. Census's Business Dynamics Statistics and prime-age population data from the Census series. Finally, we used county-level real GDP data provided by the Bureau for Economic Analysis. We present the summary statistics for these variables in Panel A of Appendix Table A.1.[8]

[7] Differentiating between multi-establishment and single-establishment firms is not the primary focus of our research, and our data limitations prevent us from doing so. Furthermore, accounting for multi-establishments within a firm would introduce additional complexities, such as determining the firm's location when its establishments are situated in different regions.

[8] Throughout this paper, employment consists of full and part-time paid employees. Population refers to

To assess economic outcomes at the ZIP code level, we used the U.S. Census's ZIP Codes Business Patterns (ZBP) data, which encompasses measurements of the number of establishments, employment, and payrolls. However, measurements for population and firm exits are not included in the ZBP at the ZIP code level.

Control Variables. Factors beyond flood risk, such as local demographic and economic circumstances can also impact county-level changes in economic performance. As a result, changes in firm dynamics, employment, and total output could be a result of these factors. To ensure that the relationship we are interested in is not influenced by additional county-level characteristics, we incorporate a set of county-level controls into our empirical analysis. Following Autor, Dorn and Hanson (2013) in creating the county-level controls, we control for the share of female labor, the manufacturing share of employment, and population density, and China's import penetration ratio. A summary of these controls can be found in Appendix Table A.1. In the change-on-change specification, we include the full set of controls including the changes in manufacturing share of employment, the changes in female share, the changes in China import penetration,[9] the changes in population density[10] and the changes in cumulative flood share.

3 Reduced-form Evidence

This section presents reduced-form results on the effects of flood risk and actual flood events. We begin by examining the influence of flood risk on firms and employment, which is a novel contribution to the literature. We do so by presenting motivational evidence (Section 3.1) and results of a formal empirical analysis (Section 3.2). In Section 3.3, we provide our

"prime age" population between 15 to 64 years.

[9]The study by Autor, Dorn and Hanson (2021) reveals that China's import penetration ratio in the U.S. experienced rapid growth from 1990 to 2010 before plateauing in 2010. This enables us to directly utilize the China import penetration ratio from the 1990–2010 period, as constructed by Autor, Dorn and Hanson (2013), to account for the influence of exposure to China's trade shocks. To avoid endogeneity issues, we construct the China import penetration ratio based on Chinese imports by other high-income countries (Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland). The changes in China import penetration is defined as changes in Chinese import exposure per worker in a region, where regional imports are calculated according to its national industry employment share.

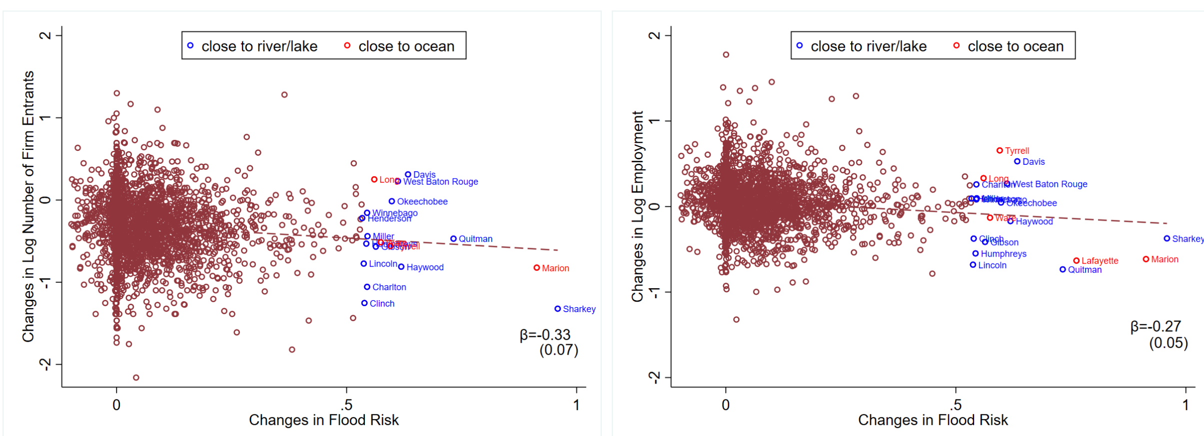
[10]Given the concern that the share of female labor and the manufacturing share of employment may be endogenous outcomes, we find that our regression results remain quantitatively similar when dropping these controls. In the regressions of using log population as the dependent variable, we do not control for population density to avoid collinearity (we instead control for initial population).

estimate of the impact of actual flood events. This helps us regulate the model parameters governing direct damages caused by floods.

3.1 Impact of Flood Risk: Motivation and Research Design

To provide motivational evidence, we analyze how changes in flood risk are related to changes in firm entry and employment in the raw data. Figure 2a displays 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, Figure 2b indicates a negative correlation between flood risk and employment changes. In the raw data, a one-standard-deviation (10-percentage-point) increase in the share of land in FEMA's flood zones is linked to a decline of 3.3% in firm entry and a decline of 2.7% in employment. Moreover, these figures reveal that counties that experienced the largest increases in flood risk are located near rivers, lakes, or oceans.

Figure 2: Correlations in the Raw Data



(a) Firm entry **(b)** Employment

Notes: The counties that experienced the highest increase in flood risk are highlighted 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).

The correlations found in the raw data suggest that increased flood risk discourages firm entry and employment. However, these relationships may be influenced by other county-level characteristics. To examine the causal impact of flood risk increase on firm entry, employment, and other outcomes, we employ a fixed effects framework that controls for various confounding factors. Our baseline empirical specification is as follows:

$$\log Y_{i,t} = \alpha + \beta_1 FloodRisk_{i,t} + \sigma_i + \gamma_{s,t} + \zeta \mathbf{X}_{i,t} + \beta_2 ActualFlood_{i,t} + \epsilon_{i,t}. \tag{1}$$

Here, $\log Y_{i,t}$ represents the logarithm of the number of firm entrants (or other outcomes of interest) in locality i (county or ZIP code) and year t. Our primary independent variable, $FloodRisk_{i,t}$, indicates the percentage of land area within FEMA's special flood zones in locality i and year t. Due to data limitations and as our interest lies in the long-run effects 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 such as industry composition that may be correlated with flood risk and outcomes. State-by-year fixed effects, $\gamma_{s,t}$, capture the statewide economic growth or business cycle fluctuations. Additionally, the vector $\mathbf{X}_{i,t}$ contains a set of county-level demographic and economic factors, as described in Section 2, that capture other factors that may confound the relationship between flood risk and county-level outcomes. To distinguish the distinct impacts of flood risk and actual flood events, we also control for $ActualFlood_{i,t}$, defined as the cumulative percentage of flooded areas for locality i in year t. Standard errors are clustered at the locality level.

3.2 Impact of Flood Risk: Empirical Findings

3.2.1 Fixed Effects Estimations

County-level Results. Panel A in Table 1 displays the county-level impact of flood risk on firm entry, firm exit, employment, population, and real GDP. The regressions in odd columns control for county fixed effects and state-by-year fixed effects. The regressions in even columns further control for time-varying county characteristics and the share of actual flooded areas, due to the concern that actual floods may drive the impact of flood risk. We find that the estimated impact of flood risk remains stable, regardless of whether we control for the occurrence of actual floods.

Table 1: 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	-0.175**	-0.169**	-0.128*	-0.111	-0.227***	-0.199***	-0.116***	-0.130***	-0.288***	-0.278***
	(0.082)	(0.080)	(0.073)	(0.074)	(0.055)	(0.054)	(0.042)	(0.042)	(0.071)	(0.070)
Observations	5072	5072	5072	5072	5072	5072	5072	5072	5072	5072
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
Other Controls		Yes		Yes		Yes		Yes		Yes
Flood Share		Yes		Yes		Yes		Yes		Yes
ymean	4.11	4.11	4.04	4.04	9.11	9.11	9.98	9.98	13.80	13.80

Panel B: ZIP Code Level

	(1)	(2)	(3)	(4)	(5)	(6)
	log(Establishment)		log(Employment)		log(Payroll)	
Flood Risk	-0.233***	-0.203***	-0.210***	-0.250***	-0.276***	-0.226***
	(0.039)	(0.039)	(0.066)	(0.066)	(0.072)	(0.073)
Observations	41032	41032	41032	41032	41032	41032
ZIP Code FE	Yes	Yes	Yes	Yes	Yes	Yes
State×YearFE	Yes	Yes	Yes	Yes	Yes	Yes
Other Controls		Yes		Yes		Yes
Flood Share		Yes		Yes		Yes
ymean	4.44	4.44	6.61	6.61	9.96	9.96

Notes: Due to data availability, we utilize county-level GDP in 2001 instead of 1998 for Columns (9) and (10), as the BEA county-level GDP data starts from 2001. The primary independent variable, Flood Risk$_{i,t}$, signifies the percentage of land area within FEMA's special flood zones in locality i and year t. We are interested in the long-run impact of flood risk, so we focus on t being 1998 and 2018. All regressions account for locality fixed effects, state-by-year fixed effects, and a comprehensive set of demographic and economic controls. Data on firm entry, exit, and population are not available at the ZIP Code level. Standard errors are clustered at the locality level (county or ZIP code). Significance levels: * 10%, ** 5%, *** 1%.

We highlight three empirical findings. First, Column (2) demonstrates that increased flood risk had a negative impact on firm entry. In terms of magnitude, a standard deviation (10-percentage-point) increase in flood risk between 1998 and 2018 reduced the number of firm entrants in 2018 by 1.7%. A county whose flood risk increase was in the 90th percentile among all counties would experience, on average, a reduction of 3.3% in firm entry. Column (4) shows that accompanying the decline in firm entry, firm exits also decreased with flood risk, although to a lesser extent than the effect on firm entry. Even though natural disasters are typically associated with more establishment closures (as we show in Section 3.3), the decrease in firm exits likely reflects the impact of fewer firms and declining firm dynamism.

Second, Columns (6) and (8) together indicate that an increase in flood risk significantly reduced employment and, to a lesser extent, population. Specifically, a one-standard-deviation (10-percentage-point) increase in flood risk reduced population by 1.3% and employment by 2.0%. The population change primarily reflects individuals' relocation, given that we control actual floods and focus on prime-age population. Our finding on the population decline in response to flood risk is consistent with the increasing displacement of people due to climate changes as reported by the United Nations,[11] and migration has been recognized by the literature as essential in understanding the long-run mitigation of natural disasters (e.g., Desmet et al., 2021). Furthermore, our results indicate that adjustments in employment to flood risk are more significant than population adjustments, suggesting that the remaining population may also modify their employment choices. Another possible explanation could be the increased separation between the locations where workers live and where they work (Monte, Redding and Rossi-Hansberg, 2018). Figure A.1 presents the bilateral commuting data, indicating that the relative number of workers who work within a county compared to workers who reside within the county does not appear to be influenced by flood risk. This suggests that commuting is unlikely to be the primary factor driving more significant responses in employment compared to population responses, which would otherwise imply a negative impact of flood risk on the relative number of workers who work within a county relative to workers who reside within the same county. 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

[11] See the report by the United Nations High Commissioner for Refugees: https://www.unhcr.org/what-we-do/build-better-futures/environment-disasters-and-climate-change/climate-change-and. A recent book, Bittle (2023), also provides numerous examples of climate migration in the United States.

that real GDP decreased by 2.8% with a one-standard-deviation increase in flood risk, implying a sizable impact on aggregate output.

ZIP-Code-Level Results. Next, we use ZIP-code-level data to leverage finer spatial variations in the changes of flood risk status and firm-level outcomes. Since information on firm entry, exit, and real GDP is unavailable at the ZIP code level, we instead focus on two related variables: the number of establishments and annual payrolls. We also omit results regarding population due to the lack of data at the ZIP-code level. We use similar specifications as before, controlling for ZIP-code-level fixed effects, state-by-year fixed effects, control variables, and actual floods. Panel B of Table 1 shows that the impact of flood risk is similar in magnitude to the county-level results when focusing on finer geographic variations. An increase in flood risk significantly decreased the number of firms, total employment, and total payrolls.

Robustness Checks. It is worth noting that a subset of counties is not included in the FEMA historic Q3 maps, and therefore, flood risk information is not available for them. To account for this, we treat the flood risk in these unreported areas as zero since firms and individuals do not receive any risk signal from FEMA. Alternatively, Appendix Table A.2 uses the counties with available FEMA flood maps for 1998 and 2018 to perform our baseline regression (1). Our findings show that the estimated impact of flood risk is qualitatively similar to our baseline results, with slightly larger magnitudes. To err on the side of caution, we use our baseline estimates to calibrate the quantitative model.

To further validate our results, we also conduct a placebo test. Instead of using the outcomes from 1998 and 2018, we investigate the impact of flood risk on firm dynamics and other county-level outcomes in the preceding period, 1990 and 1998. Intuitively, if the adverse impact of flood risk on economic outcomes during our sample period is influenced by other omitted local economic characteristics, this negative impact may have already occurred in earlier periods. As demonstrated in Appendix Table A.3, we find that this is not the case:[12] the estimates from the placebo tests are considerably smaller in magnitude and not significant, indicating that current period flood risk do not correlate with county-level outcomes in prior years. Additionally, given the concern that the changes in manufacturing

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

employment share and female share could be endogenous outcomes, we show in Table A.4 that our results remain similar when not including these controls. Our main results are robust when clustering at the state level, allowing for spatial correlation in the error terms, as shown in Table A.5.

3.2.2 LASSO-IV Estimation

In our baseline analysis, the variation in flood risk is constructed using updates based on the FEMA Flood Insurance Rate Maps (FIRM). Although FEMA flood risk ratings are directly observed by firms and workers, there are several potential measurement and endogeneity concerns associated with using FEMA FIRM map updates. Firstly, one might be concerned that the significant wave of FEMA map updates in the 2000s was subject to requests for map amendments or FEMA budgetary considerations (Pralle, 2019). Both of these factors could be driven by local economic considerations. Secondly, FEMA risk measures also suffer from measurement errors due to the utilization of outdated risk models. To address these empirical challenges, we take two approaches. First, we employ a LASSO IV approach, as specified in this subsection. Next, in Section 3.2.3, we construct an alternative measure of flood risk updates using data from First Street Foundation.

To exploit variation in flood risk updates arising from differences in geo-climatic features across counties, we begin with a set of variables[13] constructed for the initial year, 1998, using the climate reanalysis data ERA5-Land. The relationship between flood risk and geo-climatic variables is complex and potentially highly nonlinear: for example, soil temperature and evaporation rate may interact to affect flood risk of a region. These geo-climatic variables may also have heterogeneous impacts on a county's flood risk depending on the aggregate trend, which we proxy by the average change in flood risk in the rest of the state. To allow for high-dimensional interactions between climatic variables and to minimize discretion, we take a LASSO regression approach to select a set of predictors, choosing among the geo-climatic variables, the average changes in flood risk in the rest of the state, and their interactions. We then adopt a LASSO-IV approach as an alternative empirical strategy to validate our OLS estimates (Chernozhukov et al., 2018; Beraja et al., 2023). We control for the cumulative shares of flooded areas between 1998–2018 for each county in case these geo-climatic features

[13] These variables include air temperature, soil temperature, precipitation, evaporation rate, and vegetation coverage index.

Table 2: 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	-0.169**	-0.214**	-0.111	-0.124	-0.199***	-0.252***	-0.130***	-0.143***	-0.278***	-0.338***
	(0.080)	(0.089)	(0.074)	(0.082)	(0.054)	(0.060)	(0.042)	(0.044)	(0.072)	(0.072)
Observations	2536	2536	2536	2536	2536	2536	2536	2536	2536	2536
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cumulative Flood	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Specification	OLS	LASSO-IV	OLS	LASSO-IV	OLS	LASSO-IV	OLS	LASSO-IV	OLS	LASSO-IV

Notes: Outcome variables are expressed in log changes. The primary independent variable, ΔFlood Risk$_i$, denotes changes in the percentage of land area within FEMA's special flood zones in locality i between the years 1998 and 2018. "LASSO-IV" indicates our cross-fit partialing-out LASSO instrumental variable approach, employing county-level geo-climatic variables, average changes in flood risk in the rest of the state, and their interactions (selected by LASSO) as instruments. All regressions account for state fixed effects, the cumulative shares of actual flooded areas between 1998–2018, and a comprehensive set of demographic and economic controls. (Controls are included as changes.) Significance levels: * 10%, ** 5%, *** 1%.

are correlated with actual floods.

Table 2 presents the results from the LASSO-IV regressions. Table A.6 presents the selected first-stage geo-climatic predictors and their weights. For example, lower evaporation is associated with higher rates of soil saturation, whereas higher temperatures may exacerbate water runoff, thus increasing localized flooding risk. Overall, we find that the LASSO-IV estimates are comparable in magnitude to our previous fixed effects estimates. According to these estimates, a one-standard-deviation increase in flood risk reduced county-level firm entry by 2.1%, employment by 2.5%, and real GDP by 3.4%. Thus, although the flood risk measures likely reflect some unobserved factors, there does not appear to be a significant bias in our fixed effects estimates.

3.2.3 Alternative Measure of Flood Risk Updates

As discussed above, flood risk updates constructed using FEMA maps may be subject to endogeneity concerns and measurement errors (Pralle, 2019). In this subsection, we perform additional robustness checks using an alternative measure of flood risk updates, based on scientific flood-model-derived predictions from First Street Foundation (First-Street-Foundation, 2018). First Street Foundation estimates flood risk using peer-reviewed flood risk models, which mitigates concerns regarding measurement errors. Flood risk updates constructed using First Street Foundation's scientific model-based flood risk maps in 2018 are also less affected by political pressures and other local economic considerations. To the extent that the flood risk areas identified by First Street Foundation are less impacted by FEMA's mandatory flood insurance, we also interpret results under this alternative measure of flood risk update as being less affected by insurance concerns.

We construct an alternative measure of flood risk updates using Q3, FEMA's historic map from 1998,[14] and First Street Foundation flood risk map in 2018. Specifically, for each county, we calculate the change in the percentage of properties within the 100-year floodplain between 1998 and 2018. From First Street Foundation, we directly obtain publicly available, county-level flood risk measures in terms of the percentage of properties within the 100-year floodplain. We then construct the corresponding measure for 1998. Ideally, to calculate this, we would overlay the historic Q3 flood map with a spatially granular map depicting the number of properties at the grid level. We obtain the best proxy for the latter using a 250m spatial raster data of population distribution from the GHSL. The GHS-POP data is estimated using satellite remote sensing methods, informing the distribution, classification, structure, and density of built-up areas at the grid level.

The results are presented in Table 3. Compared with our baseline results in Table 2, the point estimates using the alternative, property-weighted measure based on First Street Foundation data in Table 3 are larger. In Appendix Table A.7, we employ the property-weighted flood risk variation constructed from FEMA FIRM map data in both years and obtain estimates similar to those in Table 3. These results suggest that that further considering economic activities in the flood zones would strengthen our main finding.

3.3 Impact of Flood Events

Our next step is to understand the direct damages of actual floods by examining their impact on the same outcomes as above. This exercise not only confirms the negative impact of floods, as shown in recent studies (Kocornik-Mina et al., 2020), but also enables us to calibrate the parameters that govern the direct damages of floods in the model.

We use annual information on flood events from the Dartmouth Flood Archives and

[14]FEMA's historical map from 1998 serves as the most reliable measure of historic flood risk indicators in the United States during the 1990s. Alternative flood maps from other private or academic sources were rare in the US during the 1990s. First Street Foundation does not possess a flood risk map for the 1990s. We are using the first version of the First Street Foundation flood risk maps when it became available.

Table 3: Impact of Long-run Change in Flood Risk: Property-Weighted Measure from First Street Foundation

	(1)	(2)	(3)	(4)	(5)
	Δlog(Entry)	Δlog(Exit)	Δlog(Employment)	Δlog(Population)	Δlog(Output)
ΔFlood Risk	-0.556***	-0.522***	-0.568***	-0.363***	-0.570***
	(0.109)	(0.115)	(0.082)	(0.069)	(0.134)
Observations	2817	2817	2817	2817	2817
State FE	Yes	Yes	Yes	Yes	Yes
Other Controls & FE	Yes	Yes	Yes	Yes	Yes
Cumulative Flood	Yes	Yes	Yes	Yes	Yes

Notes: Outcome variables are expressed in log changes. The primary independent variable, ΔFlood Risk$_i$, denotes changes in the percentage of properties within the 100-year floodplain in locality i between the years 1998 and 2018, determined using the historic Q3 and First Street Foundation data. All regressions account for state fixed effects, the cumulative shares of actual flooded areas between 1998–2018, and a comprehensive set of demographic and economic controls. Standard errors are clustered at the county level. Significance levels: * 10%, ** 5%, *** 1%.

estimate the impact of actual floods on economic outcomes in the same year (we also discuss lagged effects below), similar to Kocornik-Mina et al. (2020). Our specification is as follows:

$$\log Y_{i,t} = \alpha + \beta_1 Flood_{i,t} + \sigma_i + \gamma_{s,t} + \zeta \mathbf{X}_{i,t} + \epsilon_{i,t}. \tag{2}$$

Here, $\log Y_{i,t}$ represents the log number of firm entrants (or other outcomes of interest) in county i and year t. Our main independent variable, $Flood_{i,t}$, denotes the percentage of county areas that are flooded in county i and year t. As before, we control for county fixed effects (σ_i), state-by-year fixed effects ($\gamma_{s,t}$), and the set of county-level demographic composition and China's import penetration ratios by year ($\mathbf{X}_{i,t}$). Since county-level GDP data, business dynamics data, and flood data are all available for the period 2001–2018, we use a balanced panel of county-level outcomes over these 18 years for estimation. We cluster standard errors at the county level.

Table 4 presents the results, and we find that the impact of actual floods is vastly different from that of flood risk. In particular, actual floods have a negligible impact on firm entry, firm exit, employment, and population, as shown in Table 4. However, they do reduce real GDP. As seen in Column (10), a one-standard-deviation increase (0.4) in the share of flooded areas in a year significantly decreases real GDP by 0.2%. This magnitude is consistent with that found in recent literature (e.g., Henderson, Storeygard and Weil, 2012; Kocornik-Mina et al., 2020). Additionally, we find that the impact is primarily driven by the current year's flood shocks, in line with these studies. As indicated in Appendix Table A.8, lagged flood shocks from the previous year have negligible effects on real GDP losses in the current year.[15] Given these findings, the model developed in the next section considers that the impact of actual floods mainly unfolds through negative productivity impact.

Table 4: 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	0.003	0.003	-0.001	-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	49376	49376	49376	49376	49376	49376	49376	49376	49376	49376
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	4.06	4.06	4.02	4.02	9.02	9.02	9.96	9.96	13.78	13.78

Notes: Outcome variables are expressed in log values. The primary independent variable, Flood Share$_{i,t}$, denotes the percentage of flooded land area in county i during year t. We are interested in the short-run impact of yearly floods, and the sample period covers 2001–2018. All regressions account for county fixed effects, state-by-year fixed effects, and a comprehensive set of initial controls with year trends. Standard errors are clustered at the county level. Significance levels: * 10%, ** 5%, *** 1%.

4 Model

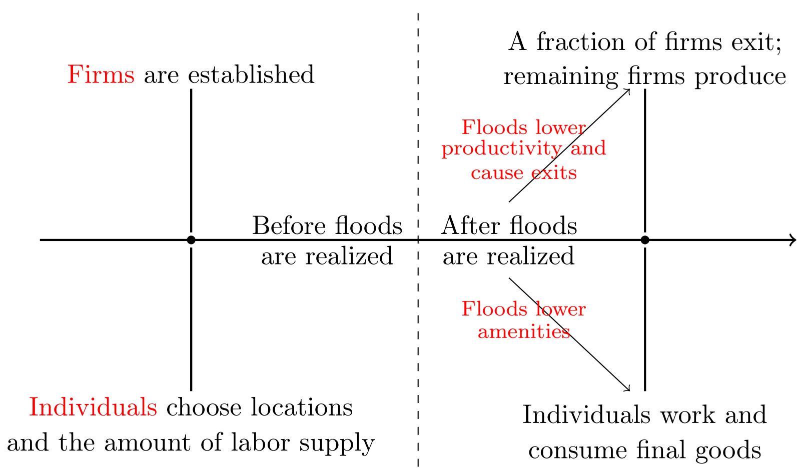
Our reduced-form analysis suggests that increased flood risk has a negative impact on long-run firm dynamism. Specifically, we observe a significant decrease in firm entry, with firm exits following to a lesser extent. Moreover, heightened flood risk leads to reduced employment levels and, to a smaller degree, decreased population. These adverse effects of flood risk are also evident in a decline in real GDP. In contrast, actual flood events mainly influence short-run productivity and have only a limited effect on firm and employment adjustments. Based on these patterns, we develop a model that takes into account firms' and workers'

[15] The literature suggests that firms may adjust their beliefs regarding climate-risk exposure based on climate disasters (e.g., Hong, Karolyi and Scheinkman, 2020; Giglio, Kelly and Stroebel, 2021; Pankratz and Schiller, 2021). However, due to the absence of data on firms' beliefs in our study, we are unable to investigate the phenomenon of belief upgrading. Nevertheless, considering the minimal delayed effects of flood events, the issue of firms' belief updating may not be a significant concern for our empirical analysis.

considerations of flood risk and actual floods in their decision-making processes.

We consider an economy consisting of M regions (indexed by m), where production in each region follows a model similar to that proposed by Krugman (1980), with free entry of firms. The total number of individuals is normalized to $\bar{L} = 1$, and individuals make decisions regarding location and labor supply to maximize their utility. We incorporate flood risk into the model as follows. Let $S = \{s_1, s_2, ...\}$ denote the set of possible states of nature, where each state s is characterized by a probability $\Pr(s)$ and a 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 previous macro models on climate change (e.g., Nordhaus, 1992; Acemoglu et al., 2012; Golosov et al., 2014; Barrage, 2020), we consider actual flood events to affect firms' average productivity and workers' average amenities within each region, as well as destructing a portion of firms. Prior to the realization of shocks, individuals make decisions regarding location and labor supply, while firms make decisions regarding entry. Once shocks occur, production and consumption take place. The timing of the model is illustrated in Figure 3, and we provide a detailed description of each activity below.

Figure 3: Timing in the Model



4.1 Production

In each region m, a composite final good is produced using differentiated varieties based on the CES technology:

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

Here, $\Omega_m(s)$ represents the set of varieties produced in region m and state s. For the sake of analytical tractability, we exclude cross-regional trade flows from our baseline model.[16] The parameter $\sigma > 1$ denotes the elasticity of substitution across varieties, and the resulting final good is used for consumption. The price index for the final good is given by:

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

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

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

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

Here, $A_m(s)$ denotes the productivity level in state s, which we assume to be $A_m(s) = \bar{A}_m \exp(-\delta \xi_m(s))$. The parameter δ governs the extent to which firm productivity levels are impacted by flooding events. In line with the growth literature (e.g., Atkeson and Burstein, 2010), we assume that an exogenous rate of $\kappa(s) = \bar{\kappa} \exp(\delta_k \xi_m(s))$ of firms exit prior to production. The parameter $\bar{\kappa}$ captures various factors, such as lawsuits or managerial shocks, that lead to the cessation of firm operations, while 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 $\tilde{\sigma} = \frac{\sigma}{\sigma-1}$ represents the constant mark-up, and $W_m(s)$ denotes the wage rate in region m. Consequently, 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 indicates that total profits are a portion $1/\sigma$ of total revenues, while the second equality arises from the cost-to-profit ratio being $(\sigma - 1)$.

[16] In Section 6.3.2, we will integrate cross-regional trade into the model and demonstrate that incorporating trade slightly strengthens the influence of floods. However, despite this effect, the economic forces within our simplified baseline model still remain the most significant determining factor.

Firms are established prior to the occurrence of shocks. In equilibrium, free entry implies that the expected costs of establishing a firm should equal the expected profits of a firm in each region:

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

In the model, we do not consider flood insurance. Since firms are risk-neutral, they will only purchase insurance if it is priced below the actuarially fair value. Assuming actuarially fair insurance in the model only reflects the expected flood damages before the occurrence of flood events and does not affect firm entry decisions. Some evidence indicates that flood insurance is priced close to fair prices. For instance, Fier, Gatzlaff and Pooser (2014) found that 80% of policyholders in the National Flood Insurance Program pay the actuarially fair premium. Additionally, a quantitative study by Fried (2021) estimates that the average price of residential flood insurance is higher than the actuarially fair value by 0.5%. Finally, it is worth noting that coverage provided by FEMA's flood insurance is limited to the repair of damaged structures and personal properties.[17] This coverage does not extend to compensating for the loss of firm productivity related to business interruption or loss of use (NFIP, 2021), which is a significant factor in our model as it affects wages and labor supply in the presence of heightened flood risk.

4.2 Individuals

We assume that individuals' utility in region m is:

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

All individuals are identical except for heterogeneous location preferences $\{v_m\}$, which are distributed according to a Fréchet distribution $G(v) = \exp(-v^{-\phi_M})$ and are i.i.d. across both regions and individuals. Location preferences are used in the literature (e.g., McFadden, 1978) to 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

[17] The maximum limit available for commercial building property coverage is $500,000.

labor disutility (e.g., Fajgelbaum et al., 2018; Bryan and Morten, 2015). The parameter $\eta > 0$ captures negative amenity shocks caused by floods, which 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, Dorn and Hanson (2013), we find that flood risk has a greater impact on employment than on population. This finding suggests that changes in local employment are not solely due to individuals' relocation but may also reflect individuals' endogenous choices of labor supply. Therefore, instead of assuming one unit of labor per individual, we introduce a positive labor supply elasticity $\phi_L > 0$.[18] For analytical tractability, we assume that labor supply l_m is determined before shocks occur, which is consistent with our empirical evidence that employment responses are mainly driven by flood risk rather than actual floods. One micro-foundation for this assumption is that, due to labor market frictions, job searches take time and cannot be completed immediately (Mortensen and Pissarides, 1994; Pissarides, 2000).

Each individual selects 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:[19]

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

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

We provide all the proofs in Appendix B.1. Therefore, ϕ_L and ϕ_M jointly determine how labor supply per individual and the number of individuals respond to changes in real wages

[18] Alternatively, we could assume employment and non-employment sectors in each region and allow individuals to choose between locations and sectors. This alternative setting would yield similar results if the elasticity of location choices in response to changes in real consumption differs from the elasticity of sector choices (e.g., Adao, Arkolakis and Esposito, 2018).

[19] The first-order condition implies that $l_m = \left(\sum_s \Pr(s) \frac{B_m(s)}{\sum_s \Pr(s) B_m(s)} \frac{W_m(s)}{\psi_m P_m(s)} \right)^{\phi_L}$. We observe that $\frac{B_m(s)}{\sum_s \Pr(s) B_m(s)}$ approaches 1 when η is small (in our calibration, $\eta = 0.002$). As a result, we consider $\frac{B_m(s)}{\sum_s \Pr(s) B_m(s)}$ to be equal to 1 in the labor supply expression, which simplifies the analytical solutions. We have also conducted numerical assessments and found that this simplification has very little impact on our quantitative findings.

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

Finally, based on individuals' optimal location and labor supply choices, we can compute individuals' welfare by evaluating the average expected utility of individuals nationwide:

$$\sum_m \Lambda_m \mathbb{E}\left[\sum_s \Pr(s) U_m(s) \middle| \text{choose region } m\right] = C\left[\sum_m \left(\sum_s \Pr(s) B_m(s) \psi_m l_m^{1+1/\phi_L}\right)^{\phi_M}\right]^{1/\phi_M} \tag{11}$$

where $C = \frac{\Gamma(1-1/\phi_M)}{1+\phi_L}$ is a constant. As demonstrated by equation (11), individuals' welfare reflects the amenity damage of floods through $B_m(s)$ and the productivity damage of floods through changes in real wages, which shape labor supply l_m as indicated by equation (9).

4.3 Equilibrium

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

$$P_m(s) L_m c_m(s) = P_m(s) Y_m(s). \tag{12}$$

The labor market clearing in region m requires:

$$N_m(s) l_m^d(s) + N_m f_m = L_m. \tag{13}$$

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

Below, we define the general equilibrium of our model:

Definition 1 *The general equilibrium consists of regional labor supply* $\{\Lambda_m, l_m\}$ *and the number of firms* N_m*, and in each state of nature* s*, individuals' 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 individuals $\{\Lambda_m, l_m\}$ is determined by individuals' expected utility maximization as given by equations (9) and (10);
(b) before shocks are realized, the number 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 equation (6);
(d) in state s, the quantity $Y_m(s)$ clears the goods market for each region, as shown in equations (12), with $P_m(s)$ as the aggregate price index given by equation (4); and
(e) in state s, wages $W_m(s)$ clear each region's labor market, as shown in equation (13).

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 the uniqueness of the equilibrium, and our calibration in the quantitative analysis satisfies this condition.

4.4 Main Forces at Work

We now demonstrate how flood risk affects aggregate productivity. Here, $r_m = \sum_s \Pr(s)\xi_m(s)$ represents the probability of a flood shock occurring in region m, which is calculated as the sum of the product of the probability of each state of nature and the corresponding flood shock occurrence in that region. In our model, by combining equations (3), (7), and (13), aggregate output can be expressed as:

$$Y_m(s) = \left(N_m(s)(A_m(s)l_m^d(s))^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}} \propto A_m(s)N_m(s)^{\frac{1}{\sigma-1}}L_m. \tag{14}$$

As the real wage per labor is equal to $Y_m(s)/L_m$, we can rearrange labor supply in equation (9) as given in equation (15):

$$l_m \propto \left(\sum_s \Pr(s)A_m(s)N_m(s)^{\frac{1}{\sigma-1}}\right)^{\phi_L}. \tag{15}$$

Here, given the "love of variety" feature of final goods, the parameter $\frac{1}{\sigma-1}$ captures the agglomeration force resulting from more varieties. To simplify our analysis, we focus on changes in flood risk in a region that accounts for a small share of the national population and therefore ignore general-equilibrium responses in individuals' utility in other regions. The population share in equation (10) is determined by:

$$\Lambda_m \propto \left(\sum_s \Pr(s) B_m(s) l_m^{1+1/\phi_L} \right)^{\phi_M}. \tag{16}$$

Finally, by noting that 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 risk. Here, we use $\hat{x} = \log(x)$ to denote the logarithm of variable x.

Proposition 2 (Responses to Changes in Flood Risk) *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:*

$$d\hat{l}_m = -\phi_L \frac{\delta + \frac{1}{\sigma-1}\bar{\kappa}\delta_\kappa + \frac{1}{\sigma-1}\phi_M \eta}{1 - \frac{1}{\sigma-1}(\phi_L + (\phi_L+1)\phi_M)} dr_m, \tag{17}$$

$$d\hat{\Lambda}_m = \phi_M \left[(1 + 1/\phi_L) d\hat{l}_m - \eta dr_m \right], \tag{18}$$

$$d\hat{L}_m = d\hat{l}_m + d\hat{\Lambda}_m, \tag{19}$$

$$d\widehat{\mathbb{E}N}_m = d\hat{L}_m - \bar{\kappa}\delta_k dr_m, \tag{20}$$

$$d\widehat{\mathbb{E}Y}_m = -\delta dr_m + d\hat{L}_m + \frac{1}{\sigma-1} d\widehat{\mathbb{E}N}_m, \tag{21}$$

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

Proof: See Appendix B.3. □

Equation (17) illustrates how the labor supply per individual responds to changes in flood risk. When the probability of flooding is higher, there is larger damage to firms' productivity, firm count, and amenity. If the agglomeration force is small such that $\frac{1}{\sigma-1}(\phi_L + (\phi_L + 1)\phi_M) < 1$, then the labor supply would decrease with higher flood risk. In this sense, our model captures the concept of "immobile labor" (Autor, Dorn and Hanson, 2013), as some individuals may respond to the shock by reducing the labor supply rather than moving to other regions. Equation (18) shows how higher flood risk induces regional relocation, as it reduces amenities and real consumption. The change in the region-level total labor supply in equation (19) includes both the effect of regional relocation and the change in labor supply per individual.

Equations (20) and (21) demonstrate the production side's response to increased flood risk. A reduced labor supply and greater damages to firm count result in fewer firms. The aggregate output is affected by three factors. First, the direct damage of floods rises with higher flood risk, which we call the *direct damage* channel. Second, increased flood risk leads to lower employment and reduced output, referred to as the *employment* channel. As mentioned earlier, employment changes stem from regional relocation (migration) and adjustments in labor supply per individual. Since output losses in out-migration regions are generally balanced by output gains in in-migration regions, the aggregate productivity effects of flood risk through regional labor relocation are relatively small compared to its local economic impacts, as illustrated in the quantitative analysis below. Finally, our model includes the *love-of-variety* channel, where aggregate output also responds to changes in the number of varieties. This channel is significant for welfare but not reflected in the GDP data (Broda and Weinstein, 2006).

5 Quantification

In this section, we calibrate our model to match the U.S. counties in 2018. Firstly, we obtain certain parameters directly from the literature and our data in Section 5.1. We then discuss how we combine the method of moments and the indirect inference approach in Sections 5.2 and 5.3 to discipline the remaining parameters and match the data moments.

Table 5: Parameter Values and Sources

Parameter	Value	Sources/Targeted Moments
Panel A: Exogenously Calibrated Parameters		
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	0.006	see regression table
δ_k—Firm exits due to flooding events	0.008	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 (0.65)	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 responses to flood risk
ϕ_M—Shape parameter of location preferences	0.84	

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

5.1 Exogenously Calibrated Parameters

Panel A of Table 5 displays the parameter values obtained directly from the literature and the data. We consider each region as a county.[20] We set the elasticity of substitution across varieties as $\sigma = 5$,[21] which is the mean estimate in the trade literature (Head and Mayer, 2014). We obtain an annual exit rate of $\bar{\kappa} = 0.08$ for the U.S. firms from the County Business Patterns data in 2018.

In our empirical analysis, we have utilized the county-year-level share of flood events from the Global Active Archive of Large Flood Events to estimate the true damages caused by these events. However, in order to apply these estimates to calibrate the actual flood damages in the quantitative model, it is crucial to ensure that both flood risk and the occurrence of flood events are measured in the same units. While areas with flood risk are defined as flood

[20]We consider all the counties with available data on population, employment, GDP, and flood risk in 2018. These counties collectively account for 96% of the U.S. aggregate GDP in 2018.

[21]By assigning an elasticity value of 5, we imply a markup rate of 0.25 for firms, calculated as $1/(\sigma - 1)$. This value falls within the range of empirical estimates found in the literature, as discussed in a comprehensive review by Basu (2019). For instance, De Loecker and Eeckhout (2017) discovered average markups ranging from 0.18 to 0.67 between 1980 and 2014 using Compustat data. Similarly, Hall (2018) found a markup ratio of 0.3 based on KLEMS productivity data from 1987 to 2015.

zones (with at least a 1% chance of being inundated by a flood event in any given year), the likelihood of these areas being flooded can exceed 1%. To maintain consistency, we adjust the data on the share of areas in flood zones by regressing the county-year-level actual shares of flooded areas observed between 2015 and 2019 against the county-level shares of areas in flood zones in 2018. Subsequently, we employ the estimated intercept and slope to convert the share of areas in flood zones into the probability of flood events, denoted as $\{r_m\}$. By our procedure, in our calibrated model, the probability $\{r_m\}$ reflects the predicted annual share of lands that would experience floods in 2018. 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, which will be used in the indirect inference to calibrate the elasticities as described below. The detailed results are provided in Appendix C.1.

We use our reduced-form evidence to inform the model parameters related to damages of flood events, namely $\{\delta, \delta_\kappa, \eta\}$. 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[22] and firm exits directly corresponds to the model parameters $\{\delta, \delta_k\}$. Using the reduced-form evidence, we obtain a productivity damage value of $\delta = 0.006$ and firm exit responses of $\delta_\kappa = 0.008$.[23] Given the lack of county-level amenity measures, we follow the approach of Barrage (2020), who demonstrated that in DICE models on temperature changes, the ratio of output damages to workers' direct utility damages is approximately 3. Therefore, we assume that $\eta = 0.002$ is roughly one-third of output damages $\delta = 0.005$. We find that the 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

Instead of directly applying the "Exact Hat Algebra" approach (Dekle, Eaton and Kortum, 2008),[24] we directly calibrate all the model parameters and solve the model using the

[22] We note that GDP data cannot capture changes in the number of varieties.

[23] Considering the potential delayed impacts of flood events, we sum up the damages from both the current period and the one-year lag period. This calculation is based on Columns (2) and (5) of Table A.8. Since the impact of floods on output in the one-year lagged period is already minimal, we do not take into account any additional lagged periods.

[24] In our model extension that incorporates bilateral trade between regions, we are unable to utilize the "Exact Hat Algebra" approach due to the lack of direct observation of the trade network between regions.

iterative algorithm developed by Alvarez and Lucas (2007). 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. Although all the parameters are jointly estimated, we can isolate the parameter that drives the identification of a given moment. Specifically, region-specific productivity $\{\bar{A}_m\}$ is identified by GDP in each region, while region-specific amenities $\{\bar{B}_m\}$ are identified by population in each region, given the real wages. Similarly, the employment-to-population ratio in each region informs the labor supply disutility $\{\psi_m\}$, and the number of firms in each region informs the entry costs $\{f_m\}$. Since 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.

We apply the indirect inference approach (Gouriéroux and Monfort, 1996)[25] 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 the actual responses.

Procedure. We jointly determine the region-specific parameters $\{\bar{A}_m, \bar{B}_m, f_m, \psi_m\}$ and labor supply elasticities $\{\phi_M, \phi_L\}$ through the following process. In the inner loop, we calibrate the region-specific parameters $\{\bar{A}_m, \bar{B}_m, f_m, \psi_m\}$ to match the GDP, population, firm count, and employment-to-population ratio in each region, given a set of $\{\phi_M, \phi_L\}$. In the outer loop, we change the probability of flood events from $\{r_m\}$ to $\{r_{m,1998}\}$. Then, we perform the same panel regressions as presented in Table 1 by regressing employment and population on flood risk (the proportion of areas within flood zones), using the model-generated data. To be conservative, we focus on our baseline estimates. Finally, we choose the labor supply elasticities $\{\phi_M, \phi_L\}$ to minimize the absolute difference between the model-generated responses and the observed coefficients.

Therefore, to ensure consistency between our baseline model and alternate model extensions, we directly calibrate the model's fundamental parameters instead of utilizing the 'Exact Hat Algebra' approach. We conducted experiments with the "Exact Hat Algebra" approach for our baseline model and found that it produced highly similar counterfactual results compared to directly calibrating the fundamental parameters.

[25] The indirect inference approach is a procedure, whereby the econometrician 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.

5.3 Calibration Results

Panel B of Table 5 displays the internally calibrated parameter values, which we find to be reasonable. For instance, the elasticity of regional population with respect to real wages, as implied by our parameters, is $\phi_M(1+\phi_L) \approx 2.1$, falling within the range of 1.1–2.5 surveyed by Fajgelbaum et al. (2018).[26] Our calibration implies that Arizona and California have high calibrated amenities, whereas the central United States has low calibrated amenities. Additionally, states like New York, California, and Washington exhibit high calibrated productivities, while states such as Mississippi and Alabama have low calibrated productivities. We observe a minimal correlation between productivities and amenities. These patterns of amenities and productivities align with the findings of Allen and Arkolakis (2014).

Although the parameter values of productivity, amenity, labor disutility, and entry costs depend on the normalization and geographic levels and, therefore, cannot be directly compared across studies, our model shows a good match with the data moments. Appendix Table C.1 compares the four sets of targeted moments (regional GDP, population, employment-to-population ratio, and firm count) predicted by our model with the corresponding data moments. The cross-regional correlation is almost unity for all sets of targeted moments, suggesting that our calibrated model matches the targeted moments very well.

Table 6 compares the actual and model-generated regression results. Columns (1) and (2) display the targeted regression coefficients, and with the calibrated structural elasticities $\{\phi_M, \phi_L\}$, our model generates similar employment and population responses to changes in the share of flood-prone areas between 1998 and 2018 as observed in the data.

Columns (3)–(5) present the non-targeted responses. Column (3) shows 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 from the ZIP-code-level estimates (see Table 1). 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. Lastly, in Column (5), we demonstrate that our model successfully reproduces the empirically observed negative relationship between

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

Table 6: Comparison of Actual and Model-generated Regression Results

	(1)	(2)	(3)	(4)	(5)
	Targeted		Non-targeted		
	log(Employment)	log(Population)	log(Output)	log(Entry)	log(Exit)
Actual Data:					
Flood risk	-0.199*** (0.054)	-0.130*** (0.042)	-0.278*** (0.070)	-0.169** (0.080)	-0.111 (0.074)
Model-generated Data:					
Flood risk	-0.203*** (0.003)	-0.120*** (0.002)	-0.209*** (0.003)	-0.203*** (0.003)	-0.198*** (0.003)

Notes: We perform the panel regression using the observed and model-generated data in 1998 and 2018, following the same specifications as in the even-numbered columns of Table 1. Significance levels: * 10%, ** 5%, *** 1%.

changes in flood risk and the average number of firm exits. Specifically, higher flood risk increases the likelihood of firm closures, given a constant number of firms. However, the rise in flood risk also deters firm entry, leading to a decrease in the overall number of firms. Our findings indicate that the combined effect of these two factors results in a net negative impact, which corresponds with the empirical evidence.

6 Counterfactual Exercises

In this section, we apply our calibrated model to study the aggregate and distributional effects of flood risk, which we present in Sections 6.1 and 6.2, respectively. In Section 6.3, we demonstrate how our quantitative results change when we extend our baseline model with richer elements. Finally, in Section 6.4, we evaluate the impact of predicted future changes in flood risk between 2020 and 2050.

6.1 Aggregate Productivity Effects of Flood Risk

Panel A of Table 7 presents the aggregate effects of flood risk in 2018, which is computed by comparing the baseline equilibrium to the counterfactual scenario with flood risk $\{r_m\}$ set to 0. We find that, in the aggregate, flood risk caused a 0.53% decline in output, as well as a

Table 7: Aggregate Effects of Flood Risk in 2018

Panel A: Aggregate Effects

	Output	Employment	Firm Entry	Firm Exits	Welfare
Overall risk in 2018	-0.53%	-0.33%	-0.30%	-0.15%	-0.52%

Panel B: Decomposition of Output Losses

	Decomposition of Output Losses			
	Direct Damage	Labor Relocation	Labor Supply	Variety Effects
Overall risk in 2018	-0.12%	0.02%	-0.31%	-0.08%

0.33% reduction in employment, a 0.30% decline in the number of firm entrants, and a 0.15% decline in the number of firm exits. Lastly, we observe that flood risk resulted in a 0.52% decrease in individuals' welfare, reflecting amenity losses from flood risk, as well as real wage losses resulting from productivity damages and reduced variety in the consumption basket.

Panel B of Table 7 decomposes the output loss into three channels—direct damages, employment, and varieties—by allowing population shares, labor supply, and the number of varieties to respond separately to flood risk.[27] We further decompose employment changes into changes in population shares (labor relocation across localities with no changes in labor supply per individual in each locality), referred to as "labor relocation," and changes in labor supply per individual, referred to as "labor supply."

The decomposition reveals that direct damages from flood risk caused a 0.12% decline in output, a magnitude similar to the estimate by FEMA (Grimm, 2020) that shows the cost of flood damage was around $17 billion annually between 2010 and 2018, accounting for approximately 0.1% of annual GDP. Direct damages represent only 23% of the overall output loss. In other words, disregarding adjustments made by workers and firms significantly underestimates the aggregate productivity loss, as demonstrated by the last three columns of Panel B in Table 7. Labor relocation had a minimal impact of 0.02% on aggregate output,

[27] 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 constant. We then allow population shares to adapt to the level observed in the hypothetical scenario where there is no flood risk. This allows us to isolate the effects of labor relocation. Subsequently, we permit labor supply to adjust to the level witnessed in the counterfactual scenario with no flood risk, thus enabling us to isolate the effects of labor supply. Finally, we compute how changes in the number of varieties in each region further alter the aggregate output.

primarily due to the offsetting effects of workers relocating across regions.[28] Output losses resulting from reduced labor supply accounted for 58% of aggregate output losses, indicating significant amplification effects of workers' endogenous labor supply, while fewer varieties due to less firm entry contributed another 15% of the aggregate output losses.

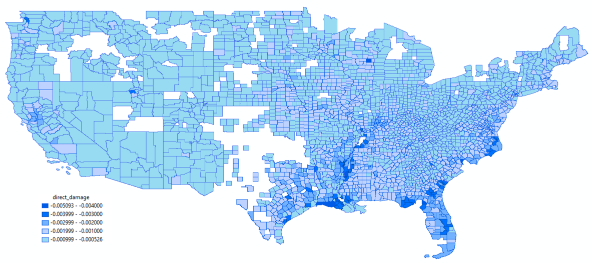
6.2 Distributional Effects of Flood Risk

Flood risk varies significantly across locations. While the output loss was 0.53% at the national level, the top 5% and top 1% counties (ranked by output losses) experienced a 9.1% and 15.9% decrease in output, respectively. This indicates substantial heterogeneity in the impact of flood risk across localities in the United States.

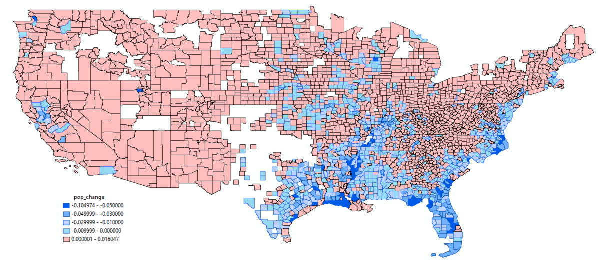
Based on the analytical result in Proposition 2, Figure 4 displays the county-level output changes decomposed into the main channels—direct damages, employment (population multiplied by labor supply per individual), and firm entry. Concerning direct damages, we observe that most counties experienced negative damages, especially those in the southern and eastern regions (particularly along the coastline), consistent with the flood risk geography shown in Figure 1. These affected counties lost population to other counties, resulting in reduced labor supply per individual and firm entry. Consistent with the significant drops in output, the upper 1% counties (ranked by corresponding losses in 2018) experienced a 7.1% decline in population, a 5.4% decrease in labor supply per individual, and a 12.5% reduction in the number of firms. However, counties that were mildly affected by flood risk (e.g., some middle Western counties) were, in fact, "winners" from the flood risk. They benefited from labor relocation from risky coastal areas, resulting in increased firm entry and labor supply per worker (as more varieties increase workers' utility).

[28] The lack of correlation between flood risk and GDP per capita at the county level leads to the conclusion that flood-induced worker reallocation across different areas may not necessarily be influential. However, there are studies, such as Bryan and Morten (2015), that indicate significant gains from reducing mobility costs in the US, suggesting that misallocation of resources across space can impact overall productivity.

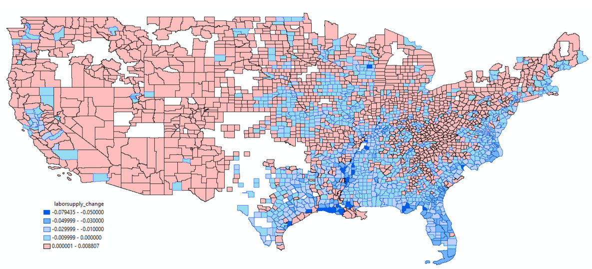
Figure 4: Distributional Effects of Flood Risk in 2018



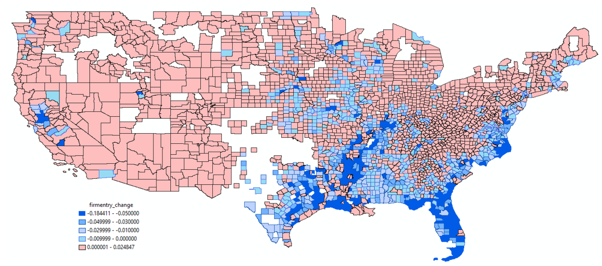
(a) Direct damages



(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, changes in firm entry mimic changes in employment because entry costs are paid in terms of a fixed amount of labor. We now experiment with an alternative assumption on firm entry costs. Following recent literature that shows creating new firms 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 than wages (final-good prices were affected not only by wages but also by firm productivity and the number of varieties). As a result of fewer firms, the output losses from the flood risk also slightly increased with the share of entry costs spent on final goods. As shown in Table 8, when entry costs were fully paid by final goods ($\alpha = 1$), the aggregate output loss from the flood risk was -0.57%, larger than the baseline result (-0.53%), which corresponds to the case where entry costs were fully paid by labor ($\alpha = 0$).

Figure 5: Entry Costs and Aggregate Impact of Flood Risk

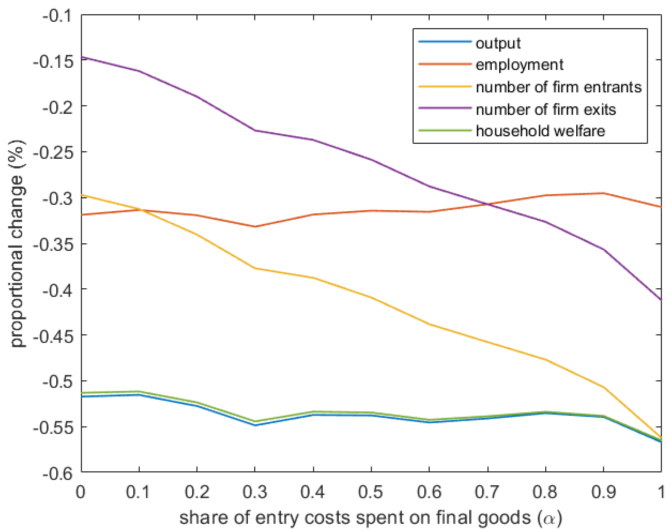


Table 8: Aggregate Impact of Flood Risk in 2018 across Different Model Specifications

	Output	Employment	Firm Entry	Firm Exits	Welfare
(1) Baseline model	-0.53%	-0.33%	-0.30%	-0.15%	-0.52%
(2) Entry costs paid in goods	-0.57%	-0.31%	-0.56%	-0.41%	-0.57%
(3) Allowing for interregional trade	-0.63%	-0.52%	-0.45%	-0.30%	-0.61%
(4) Allowing for capital & housing	-0.64%	-0.33%	-0.31%	-0.16%	-0.55%
(5) Heterogeneous firm productivity	-0.51%	-0.31%	-0.29%	-0.14%	-0.50%

6.3.2 Interregional Trade Networks

In the baseline model, we do not consider goods flows across regions. In Appendix B.4, we extend the model to include two sectors—traded and non-traded sectors—in each county. We find that holding other parameters constant, incorporating trade into the model would result in a reduced impact of floods on real wages due to reduced price volatility (as workers can source some consumption goods from non-affected regions). Consequently, employment will display a lower level of responsiveness to flood risk as well. As our calibration targets the response of employment to flood risk, 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. Since a greater labor supply elasticity generates a larger decline in aggregate labor supply resulting from increases in flood risk, the overall loss in aggregate output due to flood risk is thus slightly larger when trade is accounted for.

6.3.3 Capital and Housing

Our baseline model assumes labor as the only input in firm production. In Appendix B.5, we extend the model to include both capital and structures (housing) in firm production and also consider that housing matters for workers' utility. Capital is mobile across regions and can be rented at a constant real rate from the global market, whereas housing is supplied locally following Serrato and Zidar (2016). We recalibrate the model to the data.

As shown in Table 8, in this alternative model that considers capital and housing, the output losses due to flood risk were 0.64% in 2018, which is higher than 0.53% in our baseline model. The primary reason for the larger impact is that flood risk not only lowered employment but also decreased the capital-to-labor ratio, as capital usage became relatively more expensive than labor in the presence of flood risk.[29]

6.3.4 Heterogeneity in Firm Productivity

In our baseline model, we presumed uniformity among firms within each location. However, in reality, firms can exhibit heterogeneity in their productivity levels, making smaller firms more vulnerable to flood shocks. Acknowledging this, we adopt the Melitz (2003) approach to model the firm sector in each region, as detailed in Appendix B.6. Specifically, we assume that firms display varying productivity levels, and in addition to entry costs, they must also cover fixed operational costs to actively produce. Consequently, only unproductive (small) firms will cease operations due to their unwillingness to bear the fixed operational costs. In the recalibration of this extended model, we determine fixed operational costs and their dependence on floods to ensure that the annual exit rate is 0.08 in every location, and floods

[29] The real return of capital remained constant, while workers' real wages declined in the presence of flood risk. Quantitatively, we find that flood risk in 2018 lowered the U.S. aggregate capital-to-labor ratio by 0.37%.

result in a 0.8% increase in exits, consistent with our baseline calibration.

We discover that the quantitative outcomes of this model extension closely resemble our baseline findings, as flood-induced exits have a small magnitude. If anything, we observe that output losses from flood risk are slightly reduced in this extended model compared to our baseline results. This is because, in contrast to the baseline model that assumes homogeneous firms, exiting firms are smaller and have a lesser impact in this model extension.

Taken together, when we incorporate additional factors, these extensions indicate that flood risk may have a slightly stronger impact on the economy. However, it is essential to note that the economic forces in our baseline model still remain the main driving force behind the productivity impact of floods.

6.4 Future Changes in Flood Risk

Flood risk is likely to increase as a result of greenhouse gas emissions. To assess the impact of these potential changes in flood risk on the U.S. economy, we adjust the flood risk $\{r_m\}$ in our baseline model using First Street Foundation's county-level predictions on proportional changes in flood risk between 2020 and 2050. On average, the proportion of properties at risk of flooding is expected to rise by 4.5% between 2020 and 2050.

According to the data presented in Table 9, the projected rise in flood risk from 2020 to 2050 is expected to cause a 0.13% decline in aggregate output. This decline is not large considering the relatively limited increase in flood risk during the same period. Our projected output loss is comparable to that of Desmet et al. (2021), who demonstrate that sea level rise due to climate changes will lead to a 0.11% loss in global real GDP in the next century. As previously, only 10% of the output losses arise from direct damages.[30] The remaining output losses stem from reduced labor supply and firm entry, highlighting the significance of accounting for the long-run adjustments of workers and firms.

[30] In comparison with the flood risk in 2018, the role of direct damages in output losses is reduced. This is because the predicted increase in 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).

Table 9: Aggregate Effects of Future Changes in Flood Risk, 2020–2050

Panel A: Aggregate Effects					
	Output	Employment	Firm Entry	Firm Exits	Welfare
Changes in risk, 2020–2050	-0.135%	-0.057%	-0.053%	-0.037%	-0.055%

Panel B: Decomposition of Output Losses				
	Decomposition of Output Losses			
	Direct Damage	Labor Relocation	Labor Supply	Variety Effects
Changes in risk, 2020–2050	-0.013%	-0.038%	-0.058%	-0.026%

7 Conclusion

Using recently available data, we demonstrate that increasing flood risk has a large negative impact on firm entry, employment, and output in the long run, whereas flood events reduce output in the short run. Building on these findings, we develop and apply a spatial equilibrium model to estimate the aggregate impact of increasing flood risk. In our model, firms decide whether to enter a locality, taking into account the expected flood risk, while workers decide whether to relocate and how much labor to supply. Realized floods affect the average productivity of firms and the average amenity of workers in a given locality. Quantitatively, we find that flood risk reduced U.S. aggregate output by 0.53% in 2018, with 77% of the loss arising from the long-run adjustments of firms and workers in response to risk and 23% from direct damages.

While our analysis focuses solely on flood risk in the U.S. to leverage systematic data for measuring flood risk, our methodology can be extended to the study of other natural disasters in diverse contexts. Our findings underscore that accounting only for direct damages significantly underestimates the actual losses associated with natural disasters, as firms and workers rationally adjust their economic activities in anticipation of these risks. Therefore, any policy aimed at reducing climate damages needs to consider the long-run adaptations of firms and workers. Our results also emphasize the importance of incorporating endogenous general equilibrium responses to flood risk in evaluating the cost of natural disasters.

References

Acemoglu, Daron, and Dan Cao. 2015. "Innovation by Entrants and Incumbents." *Journal of Economic Theory*, 157: 255–294.

Acemoglu, Daron, Philippe Aghion, Leonardo Bursztyn, and David Hemous. 2012. "The Environment and Directed Technical Change." *American Economic Review*, 102(1).

Adao, Rodrigo, Costas Arkolakis, and Federico Esposito. 2018. "Spatial Linkages, Global Shocks, and Local Labor Markets: Theory and Evidence." *NBER Working Paper 25544*.

AECOM. 2013. "The Impact of Climate Change and Population Growth on the National Flood Insurance Program through 2100."

Allen, Treb, and Costas Arkolakis. 2014. "Trade and the Topography of the Spatial Economy." *The Quarterly Journal of Economics*, 129(3): 1085–1140.

Allen, Treb, Costas Arkolakis, and Xiangliang Li. 2015. "A Note on the Existence and Uniqueness of Trade Equilibria." *Working Paper.*

Alvarez, Fernando, and Jr Robert E Lucas. 2007. "General Equilibrium Analysis of the Eaton–Kortum Model of International Trade." *Journal of Monetary Economics*, 54(6).

Alvarez, Jose Luis Cruz, and Esteban Rossi-Hansberg. 2021. "The Economic Geography of Global Warming." *NBER Working Paper 28466.*

Atkeson, Andrew, and Ariel Burstein. 2010. "Innovation, Firm Dynamics, and International Trade." *Journal of Political Economy*, 118(3).

Autor, David, David Dorn, and Gordon Hanson. 2021. "On the Persistence of the China Shock." *Brookings Papers on Economic Activity*, 2021(2).

Autor, David H, David Dorn, and Gordon H Hanson. 2013. "The China Syndrome: Local Labor Market Effects of Import Competition in the United States." *The American Economic Review*, 103(6).

Bakkensen, Laura A, and Lint Barrage. 2021. "Flood Risk Belief Heterogeneity and Coastal Home Price Dynamics: Going under Water?" *NBER Working Paper 23854*.

Bakkensen, Laura, and Lint Barrage. 2018. "Climate Shocks, Cyclones, and Economic Growth: Bridging the Micro-Macro Gap." *NBER Working Paper*, 24893.

Balboni, Clare. 2019. "In Harm's Way? Infrastructure Investments and the Persistence of Coastal Cities." *Working Paper*.

Bansal, Ravi, and Marcelo Ochoa. 2011. "Temperature, Aggregate Risk, and Expected Returns." *NBER Working Paper*, 17575.

Barrage, Lint. 2020. "Optimal Dynamic Carbon Taxes in a Climate–Economy Model with Distortionary Fiscal Policy." *Review of Economic Studies*, 87(1).

Basu, Susanto. 2019. "Are Price-Cost Markups Rising in the United States? A Discussion of the Evidence." *Journal of Economic Perspectives*, 33(3): 3–22.

Beraja, Martin, Andrew Kao, David Y Yang, and Noam Yuchtman. 2023. "AI-tocracy." *The Quarterly Journal of Economics*, 138(3): 1349–1402.

Bilal, Adrien, and Esteban Rossi-Hansberg. 2023. "Anticipating Climate Change Across the United States." National Bureau of Economic Research.

Bittle, Jake. 2023. *The Great Displacement: Climate Change and the Next American Migration.* Simon & Schuster.

Broda, Christian, and D. E. Weinstein. 2006. "Globalization and the Gains from Trade." *The Quarterly Journal of Economics*, 121(2).

Bryan, Gharad, and Melanie Morten. 2015. "Economic Development and the Spatial Allocation of Labor: Evidence From Indonesia." *Working Paper*.

Burke, Marshall, Solomon M. Hsiang, and Edward Miguel. 2015. "Global Non-linear Effect of Temperature on Economic Production." *Nature*, 527: 235–239.

Caselli, F., and W. J. Coleman. 2001. "The U.S. Structural Transformation and Regional Convergence: A Reinterpretation." *Journal of Political Economy*, 109(3).

Castro-Vincenzi, Juanma. 2023. "Climate hazards and resilience in the global car industry." Technical report, Working Paper.

Chaney, Thomas. 2008. "Distorted gravity: the intensive and extensive margins of international trade." *American Economic Review*, 98(4): 1707–21.

Chernozhukov, Victor, Denis Chetverikov, Mert Demirer, Esther Duflo, Chris-

tian Hansen, Whitney Newey, and James Robins. 2018. "Double/debiased machine learning for treatment and structural parameters."

Costinot, Arnaud, Dave Donaldson, and Cory Smith. 2016. "Evolving Comparative Advantage and the Impact of Climate Change in Agricultural Markets: Evidence from 1.7 Million Fields around the World." *Journal of Political Economy*, 124(1).

Dekle, Robert, Jonathan Eaton, and Samuel Kortum. 2008. "Global Rebalancing with Gravity: Measuring the Burden of Adjustment." *IMF Staff Papers*, 55(3): 511–40.

Dell, Melissa, Benjamin F. Jones, and Benjamin A. Olken. 2012. "Temperature Shocks and Economic Growth: Evidence from the Last Half Century." *American Economic Journal: Macroeconomics*, 4(3): 65–99.

Dell, Melissa, Benjamin F. Jones, and Benjamin A. Olken. 2014. "What Do We Learn from the Weather? The New Climate–Economy Literature." *Journal of Economic Literature*, 52(3).

De Loecker, Jan, and Jan Eeckhout. 2017. "The Rise of Market Power and the Macroeconomic Implications." *NBER Working Paper*, 23687.

Deryugina, Tatyana. 2017. "The Fiscal Cost of Hurricanes: Disaster Aid versus Social Insurance." *American Economic Journal: Economic Policy*, 9(3).

Desmet, Klaus, Robert E. Kopp, Scott A. Kulp, Michael Oppenheimer Dávid Krisztián Nagy, Esteban Rossi-Hansberg, and Benjamin H. Strauss. 2021. "Evaluating the Economic Cost of Coastal Flooding." *American Economic Journal: Macroeconomics*, 13(2).

Fajgelbaum, Pablo D, Eduardo Morales, Juan Carlos Suarez Serrato, and Owen M Zidar. 2018. "State Taxes and Spatial Misallocation." *Review of Economic Studies*, 86(1).

Fajgelbaum, Pablo D. Gaubert, Cecile. 2020. "Optimal Spatial Policies, Geography and Sorting ." *The Quarterly Journal of Economics*, 135(2).

Feenstra, Robert C., Robert Inklaar, and Marcel P. Timmer. 2015. "The Next Generation of the Penn World Table." *American Economic Review*, 105(10).

Fier, Stephen G., Kevin M. Gatzlaff, and David M. Pooser. 2014. "The State of the National Flood Insurance Program: Treading Water or Sinking Fast?" *Journal of*

Insurance Regulation.

First-Street-Foundation. 2018. "First Street Foundation Aggregated Flood Risk Summary Statistics V1.2 [Data set]. Zenodo." https://zenodo.org/record/6498206.

Flavelle, Christopher, Denise Lu, Veronica Penney, Nadja Popovich, and John Schwartz. 2020. "New Data Reveals Hidden Flood Risk across America." *The New York Times*, 29.

Fried, Stephie. 2021. "Seawalls and Stilts: A Quantitative Macro Study of Climate Adaptation." *Review of Economic Studies.*

Gallagher, Justin. 2014. "Learning about an Infrequent Event: Evidence from Flood Insurance Take-Up in the United States." *American Economic Journal: Applied Economics*, 6(3).

Giglio, Stefano, Bryan Kelly, and Johannes Stroebel. 2021. "Climate Finance." *Annual Review of Financial Economics*, 13: 15–36.

Golosov, Mikhail, John Hassler, Per Krusell, and Aleh Tsyvinski. 2014. "Optimal Taxes on Fossil Fuel in General Equilibrium." *Econometrica*, 82(1).

Gouriéroux, Christian, and Alain Monfort. 1996. *Simulated-based Econometric Methods.* Oxford University Press.

Grimm, Michael. 2020. "Michael Grimm's Testimony." *Federal Emergency Management Agency.*

Hall, Robert E. 2018. "New Evidence on the Markup of Prices over Marginal Costs and the Role of Mega-Firms in the US Economy." *Working Paper.*

Head, Keith, and Thierry Mayer. 2014. "Gravity Equations: Workhorse, Toolkit, and Cookbook." *Handbook of International Economics*, 4.

Henderson, J Vernon, Adam Storeygard, and David N Weil. 2012. "Measuring Economic Growth from Outer Space." *American Economic Review*, 102(2).

Hino, Miyuki, and Marshall Burke. 2020. "Does Information about Climate Risk Affect Property Values?" *NBER Working Paper 26807.*

Hong, Harrison, G Andrew Karolyi, and José A Scheinkman. 2020. "Climate Finance." *The Review of Financial Studies*, 33(3): 1011–1023.

Hsiang, Solomon M., and Amir S. Jina. 2014. "The Causal Effect of Environmental Catastrophe on Long-Run Economic Growth: Evidence From 6,700 Cyclones." *NBER Working Paper 20352*.

Hsiang, Solomon, Robert Kopp, Amir Jina, James Rising, Michael Delgado, Shashank Mohan, D. J. Rasmussen, Robert Muir-Wood, Paul Wilson, Michael Oppenheimer, Kate Larsen, and Trevor Houser. 2017. "Estimating Economic Damage from Climate Change in the United States." *Science*, 356.

Kocornik-Mina, Adriana, Thomas K. J. McDermott, Guy Michaels, and Ferdinand Rauch. 2020. "Flooded Cities." *American Economic Journal: Applied Economics*, 12(2).

Kousky, Carolyn. 2018. "Financing Flood Losses: A Discussion of the National Flood Insurance Program." *Risk Management and Insurance Review*, 21(1).

Krugman, Paul. 1980. "Scale Economies, Product Differentiation, and the Pattern of Trade." *American Economic Review*, 70(5).

Leduc, Sylvain, and Daniel J Wilson. 2023. "Climate Change and the Geography of the US Economy."

Lin, Yatang, Thomas KJ McDermott, and Guy Michaels. 2021. "Cities and the Sea Level." *CESifo Working Paper 8997*.

McFadden, Daniel. 1978. "Modeling the Choice of Residential Location." *Transportation Research Record*, 672.

Melitz, Marc J. 2003. "The impact of trade on intra-industry reallocations and aggregate industry productivity." *Econometrica*, 71(6): 1695–1725.

Monte, Ferdinando, Stephen Redding, and Esteban Rossi-Hansberg. 2018. "Commuting, Migration, and Local Employment Elasticities." *American Economic Review*, 108(12): 3855–3890.

Mortensen, Dale, and Christopher Pissarides. 1994. "Job Creation and Job Destruction in the Theory of Unemployment." *Review of Economic Studies*, 61(3).

Mulder, Philip. 2021. "Mismeasuring Risk: The Welfare Effects of Flood Risk Information." *Working Paper*.

Nath, Ishan. 2022. "Climate change, the food problem, and the challenge of adaptation through sectoral reallocation." *Working Paper.*

Nath, Ishan B., Valerie A. Ramey, and Peter J. Klenow. 2023. "How will Global Warming Cool Economic Growth." *Working Paper.*

NFIP. 2021. "National Flood Insurance Program: Summary of Coverage for Commercial Property." https://agents.floodsmart.gov/sites/default/files/fema_summary-of-coverage-for-commercial-property_brochure_09-2021_0.pdf.

Nordhaus, William D. 1992. "An Optimal Transition Path for Controlling Greenhouse Gases." *Science*, 258.

Pankratz, Nora M. C., and Christoph Schiller. 2021. "Climate Change and Adaptation in Global Supply-Chain Networks." *Proceedings of Paris December 2019 Finance Meeting EUROFIDAI - ESSEC, European Corporate Governance Institute – Finance Working Paper No. 775/2021.*

Pissarides, Christopher. 2000. *Equilibrium Unemployment Theory (2nd ed.).* MIT Press.

Pralle, Sarah. 2019. "Drawing lines: FEMA and the politics of mapping flood zones." *Climatic Change*, 152(2): 227–237.

Rudik, Ivan. 2020. "Optimal climate policy when damages are unknown." *American Economic Journal: Economic Policy*, 12(2): 340–73.

Rudik, Ivan, Gary Lyn, Weiliang Tan, and Ariel Ortiz-Bobea. 2022. "The economic effects of climate change in dynamic spatial equilibrium."

Serrato, Juan Carlos Suarez, and Owen Zidar. 2016. "Who Benefits from State Corporate Tax Cuts? A Local Labor Markets Approach with Heterogeneous Firms." *American Economic Review*, 106(9).

Simonovska, Ina, and Michael E Waugh. 2014. "The elasticity of trade: Estimates and evidence." *Journal of International Economics*, 92(1): 34–50.

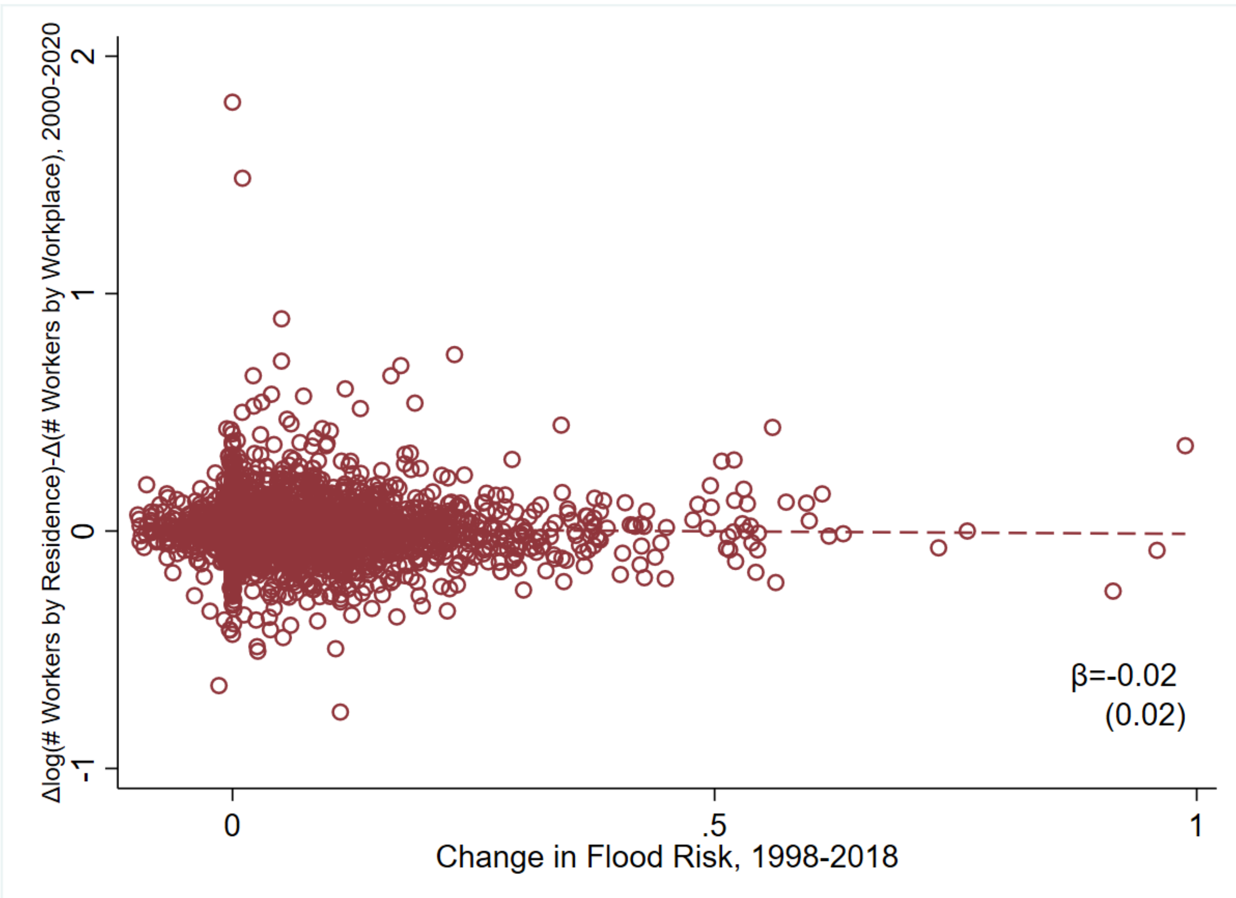
Tran, Brigitte Roth, and Daniel J Wilson. 2021. "The Local Economic Impact of Natural Disasters." *Federal Reserve Bank of San Francisco Working Paper 2020-34*.

Wagner, Katherine RH. 2022. "Adaptation and adverse selection in markets for natural disaster insurance." *American Economic Journal: Economic Policy*, 14(3): 380–421.

Appendix for Online Publication

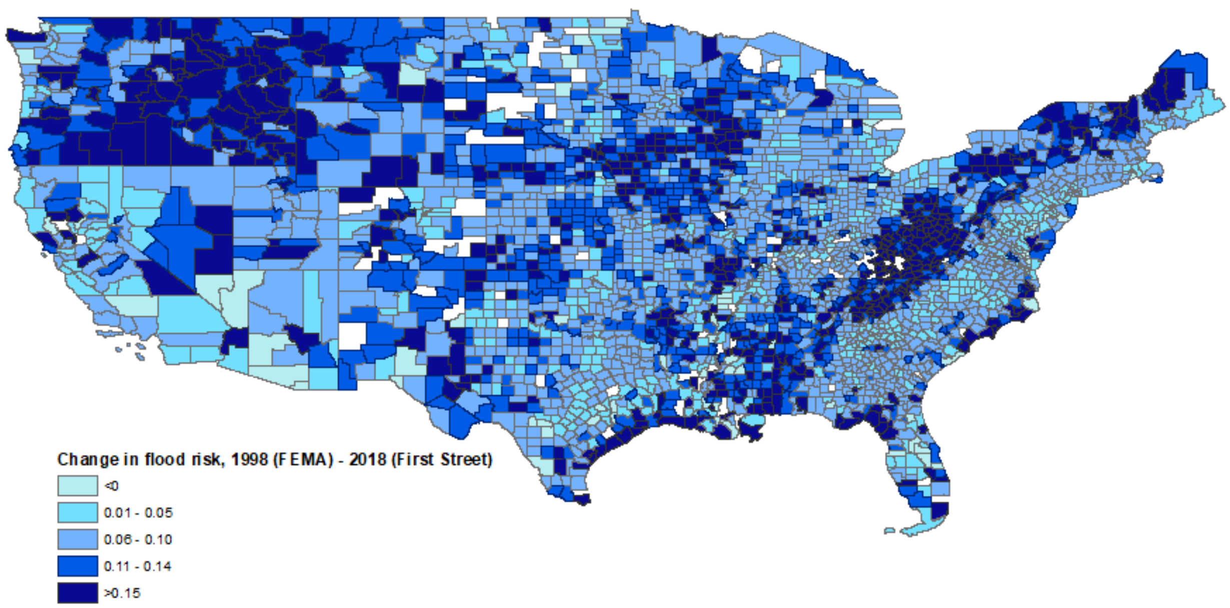
A Reduced-form Evidence: Additional Results

Figure A.1: Log Changes in Number of Workers by Residence Relative to Number of Workers by Workplace, County-level



Notes: Flood risk at the county level is measured by the percentage of the share of land areas within the 100-year floodplain. In order to gather data on commuting flows between counties, we utilize two data sources: the Census for 2000 and the 2016-2020 5-Year ACS Commuting Flows for 2020. By aggregating these commuting flows, we calculate the number of workers residing in each county (regardless of their workplace locations), as well as the number of workers employed within each county (regardless of their residence locations), for both 2000 and 2020.

Figure A.2: Change in Flood Risk, County-Level, 1998 (FEMA) and 2018 (First Street Foundation)



Notes: Flood risk at the county level is measured by the percentage of properties within the 100-year floodplain. The map illustrates the changes in the proportion of properties within the 100-year floodplain between 1998 and 2018 for each county. Blank areas on the map indicate regions without flood map coverage based on First Street Foundation's maps accessed in 2018. First-Street-Foundation (2018): v1.2.

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	4.27	4.13	9.09	9.93	13.65
	(1.39)	(1.36)	(1.55)	(1.19)	(1.52)
Year = 2018	3.94	3.94	9.14	10.03	13.96
	(1.51)	(1.47)	(1.64)	(1.39)	(1.54)

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		36	0.31
	(0.15)	(0.02)		(167)	(0.44)
Year = 2018	0.16	0.50	26.16	60	5.09
	(0.13)	(0.02)	(10.83)	(361)	(3.13)

Panel C: Independent Variables

	(1) Flood Risk	(2) Flood Share[b]
Year = 1998	0.06	0.07
	(0.24)	0.24
Year = 2018	0.12	0.24
	(0.13)	(0.40)

Notes: a: As the BEA county-level GDP data commences from 2001, we consider 2001 as the initial year for log(Real GDP), rather than 1998. b: For similar reasons, we focus on a balanced panel from 2001-2008 for results on yearly flood events. We consider 2001 as the initial year for log(flood share), rather than 1998. Employment consists of full and part-time paid employees. Population refers to "prime age" population between 15 to 64 years. The changes in China import penetration is defined as changes in Chinese import exposure per worker in a region, where regional imports are calculated according to its national industry employment share (Autor, Dorn and Hanson, 2013). Data sources: Bureau of Economic Analysis, the U.S. Census data series and Autor, Dorn and Hanson (2013). Standard deviations are provided in parentheses.

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

	(1) log(Entry)	(2) log(Exit)	(3) log(Employment)	(4) log(Population)	(5) log(Output)
Flood Risk	-0.341**	-0.208	-0.327***	-0.226**	-0.236*
	(0.150)	(0.159)	(0.115)	(0.105)	(0.131)
Observations	2260	2260	2260	2260	2260
County FE	Yes	Yes	Yes	Yes	Yes
State×Year	Yes	Yes	Yes	Yes	Yes
Other Controls	Yes	Yes	Yes	Yes	Yes
Flood Share	Yes	Yes	Yes	Yes	Yes

Notes: The sample is restricted to counties with available Q3 maps in 1998. Outcome variables are represented in log values. The primary independent variable, Flood Risk$_{i,t}$, signifies the percentage of land area within FEMA's special flood zones in county i and year t. We are interested in the long-run impact of flood risk, so we focus on t being 1998 and 2018. All regressions account for locality fixed effects, state-by-year fixed effects, and a comprehensive set of demographic and economic controls. Standard errors are clustered at the county level. Significance levels: * 10%, ** 5%, *** 1%.

Table A.3: The Impact of Long-run Change in Flood Risk: Fixed Effects Estimates, Q3, Placebo

	(1)	(2)	(3)	(4)
	log(Entry)	log(Exit)	log(Employment)	log(Population)
Flood Risk	-0.0816	0.0255	-0.0908	-0.0232
	(0.129)	(0.132)	(0.088)	(0.087)
Observations	2330	2330	2330	2330
County FE	Yes	Yes	Yes	Yes
State×Year	Yes	Yes	Yes	Yes
Other Controls	Yes	Yes	Yes	Yes
Flood Share	Yes	Yes	Yes	Yes

Notes: The sample incorporates placebo tests with prior period outcome data in 1990 and 1998, and flood risk data in 1998 and 2018. The regressions include counties with available Q3 maps in 1998. Outcome variables are expressed in log changes. The primary independent variable, Flood Risk$_{i,t}$, signifies the percentage of land area within FEMA's special flood zones in county i and year t. All regressions account for locality fixed effects, state-by-year fixed effects, and a comprehensive set of demographic and economic controls. Standard errors are clustered at the county level. Significance levels: * 10%, ** 5%, *** 1%.

Table A.4: The Impact of Long-run Change in Flood Risk: Fixed Effects Estimates, Fewer Controls

	(1)	(2)	(3)	(4)	(5)
	log(Entry)	log(Exit)	log(Employment)	log(Population)	log(Output)
Flood Risk	-0.187**	-0.133*	-0.232***	-0.128***	-0.289***
	(0.082)	(0.074)	(0.056)	(0.043)	(0.071)
Observations	5072	5072	5072	5072	5072
County FE	Yes	Yes	Yes	Yes	Yes
State×Year	Yes	Yes	Yes	Yes	Yes
Other Controls	Yes	Yes	Yes	Yes	Yes
Flood Share	Yes	Yes	Yes	Yes	Yes

Notes: Outcome variables are represented in log values. The primary independent variable, Flood Risk$_{i,t}$, signifies the percentage of land area within FEMA's special flood zones in county i and year t. We are interested in the long-run impact of flood risk, so we focus on t being 1998 and 2018. All regressions account for county fixed effects, state-by-year fixed effects, the cumulative shares of actual flooded areas between 1998–2018, the China import penetration ratio and population density. Given the concern that manufacturing employment share and changes in female share could be endogenous outcomes, these variables are not included as controls. Standard errors are clustered at the county level. Significance levels: * 10%, ** 5%, *** 1%.

Table A.5: The Impact of Long-run Change in Flood Risk: Fixed Effects Estimates, State-Level Clustering

	(1)	(2)	(3)	(4)	(5)
	log(Entry)	log(Exit)	log(Employment)	log(Population)	log(Output)
Flood Risk	-0.169*	-0.111	-0.199***	-0.130**	-0.278***
	(0.096)	(0.086)	(0.057)	(0.059)	(0.073)
Observations	5072	5072	5072	5072	5072
County FE	Yes	Yes	Yes	Yes	Yes
State×Year	Yes	Yes	Yes	Yes	Yes
Other Controls	Yes	Yes	Yes	Yes	Yes
Flood Share	Yes	Yes	Yes	Yes	Yes

Notes: Outcome variables are represented in log values. The primary independent variable, Flood Risk$_{i,t}$, signifies the percentage of land area within FEMA's special flood zones in county i and year t. We are interested in the long-run impact of flood risk, so we focus on t being 1998 and 2018. All regressions account for county fixed effects, state-by-year fixed effects, the cumulative shares of actual flooded areas between 1998–2018, and a comprehensive set of demographic and economic controls. Standard errors are clustered at the state level. Significance levels: * 10%, ** 5%, *** 1%.

Table A.6: First-stage Selected Geo-climatic Variables Based on LASSO-IV

	Cross-fitting fold #									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\Delta state\_risk$	-0.040	-0.034	-0.041	-0.040	-0.040	-0.041	-0.040	-0.041	-0.040	-0.040
$\Delta state\_risk * \Delta state\_risk$	-0.025	-0.040	-0.022	-0.022	-0.023	-0.021	-0.023	-0.022	-0.023	-0.024
$evaporation^2 * \Delta state\_risk^2$	-0.001		-0.001	-0.001	-0.001	-0.001		-0.002	-0.001	-0.001
$temperature$	0.000	0.001	0.000	0.001	0.000	0.000	0.000	0.001	0.001	0.000
$temperature * evaporation$	0.000	0.000	0.000		0.000	0.000				0.000
$evaporation^2$		-0.001								

Notes: This table displays the first-stage geo-climatic instruments with their corresponding weights for each fold in the cross-fit partialing-out LASSO-IV algorithm. Temperature denotes air temperature, and evaporation denotes the accumulated water evaporated from land surface. $\Delta state\_risk$ denotes changes in flood risk in the rest of the state from 1998 to 2018.

Table A.7: Impact of Long-run Change in Flood Risk: Property-weighted Measure from FEMA

	(1)	(2)	(3)	(4)	(5)
	Δlog(Entry)	Δlog(Exit)	Δlog(Employment)	Δlog(Population)	Δlog(Output)
ΔFlood Risk	-0.562***	-0.530***	-0.610***	-0.403***	-0.462***
	(0.142)	(0.141)	(0.097)	(0.069)	(0.155)
Observations	2812	2812	2812	2812	2812
State FE	Yes	Yes	Yes	Yes	Yes
Other Controls & FE	Yes	Yes	Yes	Yes	Yes
Flood Share	Yes	Yes	Yes	Yes	Yes

Notes: Outcome variables are expressed in log changes. The main independent variable, ΔFlood Risk$_i$, indicates changes in the percentage of properties within the 100-year floodplain in locality i between 1998 and 2018, determined using the historic Q3 and current FEMA FIRM maps. All regressions control for state fixed effects, actual flooded area, and an extensive set of demographic and economic controls. Standard errors are clustered at the county level. Significance levels: * 10%, ** 5%, *** 1%.

Table A.8: 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	0.001	0.003	-0.001	0.001***	-0.005***
	(0.004)	(0.004)	(0.001)	(0.000)	(0.002)
L.Flood Share	-0.004	0.005	0.000	-0.000	-0.001
	(0.004)	(0.004)	(0.001)	(0.000)	(0.001)
Observations	49376	49376	49376	49376	49376
County FE	Yes	Yes	Yes	Yes	Yes
State×Year FE	Yes	Yes	Yes	Yes	Yes
Initial Controls & Trends	Yes	Yes	Yes	Yes	Yes
ymean	4.06	4.02	9.02	9.96	13.78

Notes: Outcome variables are represented in log terms. The primary independent variable, Flood Share$_{i,t}$, denotes the percentage of land area flooded in county i during year t. We are interested in the short-run impact of yearly floods, and the sample period covers 2001–2018. All regressions account for county fixed effects, state-by-year fixed effects, and a comprehensive set of initial controls with year trends. Standard errors are clustered at the county level. Significance levels: * 10%, ** 5%, *** 1%.

B Proofs

B.1 Labor Supply and Location Choices

We first obtain the optimal labor supply l_m for individuals that stay in m. Individuals' 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, $\prod_{n\neq m} G_n\left(\frac{v_m x_m}{x_n}\right)$,[31]

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

over the distribution of location preference v_m. The second equality uses the cumulative and 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).

The average expected utility of individuals in nationwide is given by:

$$\begin{aligned}
&\sum_m \Lambda_m \mathbb{E}\left[\sum_s \Pr(s) U_m(s) \Big| \text{choose region } m\right] \\
&= \sum_m \Lambda_m \frac{\int_0^\infty v_m x_m \prod_{n \neq m} G_n\left(\frac{v_m x_m}{x_n}\right) g_m(v_m) dv_m}{\int_0^\infty \prod_{n \neq m} G_n\left(\frac{v_m x_m}{x_n}\right) g_m(v_m) dv_m} \\
&= \sum_m \Lambda_m \frac{\int_0^\infty x_m v_m \exp\left(-\sum_n \left(\frac{x_m}{x_n}\right)^{-\phi_M} v_m^{-\phi_M}\right) \phi_M v_m^{-\phi_M - 1} dv_m}{\Lambda_m} \\
&= \sum_m \Lambda_m \frac{x_m \int_0^\infty \left(\sum_n \left(\frac{x_m}{x_n}\right)^{-\phi_M}\right)^{1/\phi_M} y^{-1/\phi_M} \exp(-y) \frac{1}{\sum_n \left(\frac{x_m}{x_n}\right)^{-\phi_M}} dy}{\Lambda_m} \\
&= \sum_m \Lambda_m \left(\sum_n x_n^{\phi_M}\right)^{1/\phi_M} \int_0^\infty y^{-1/\phi_M} \exp(-y) dy = \Gamma\left(1 - \frac{1}{\phi_M}\right) \left(\sum_n x_n^{\phi_M}\right)^{1/\phi_M}.
\end{aligned} \tag{B.5}$$

$\Gamma(\cdot)$ is the gamma function. The first equality follows from the definition of average utility for individuals in region m, and the second equality uses the distribution of location preferences as well as the formula for location choices in equation (B.4). The third equality applies the exchange of variables $y = \sum_n \left(\frac{x_m}{x_n}\right)^{-\phi_M} v_m^{-\phi_M}$, and the final line simplifies the formula. By plugging x_n into equation (B.5), we complete the proof.

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.

$$l_m \propto (\Lambda_m)^{\frac{\frac{\phi_L}{\sigma-1}}{1-\frac{\phi_L}{\sigma-1}}} \tag{B.6}$$

Plugging l_m into equation (10), we obtain:

$$\Lambda_m = \frac{C_m \left(\Lambda_m\right)^{\frac{\phi_M(1+\phi_L)}{\sigma-1-\phi_L}}}{\sum_{m'} C_{m'} \left(\Lambda_{m'}\right)^{\frac{\phi_M(1+\phi_L)}{\sigma-1-\phi_L}}} \tag{B.7}$$

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.7) yields a unique solution of $\{\Lambda_m\}$. To make progress, define $x_{m,1} = \Lambda_m$ and $x_{m,2} = \sum_{m'} C_{m'} \left(\Lambda_{m'}\right)^{\delta}$. Then equation (B.7) can be reformulated by a system of equations:

$$x_{m,1} = C_m x_{m,1}^{\delta} x_{m,2}^{-1}, \tag{B.8}$$

$$x_{m,2} = \sum_{m'} C_{m'} x_{m',1}^{\delta}. \tag{B.9}$$

Then we can apply Theorem 1 in Allen, Arkolakis and Li (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, Arkolakis and Li (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.6), and aggregate output is determined by equation (14).

B.3 Proof of Proposition 2

We first take a log-linearization of equation (16) and then take the full derivative of it:

$$d\hat{\Lambda}_m = \phi_M \left[(1 + 1/\phi_L) d\hat{l}_m - \eta d r_m \right]. \tag{B.10}$$

Thus, we obtain equation (18). Noting that $L_m \propto \Lambda_m l_m$ and $N_m(s) \propto L_m(1-\kappa(s))$ and given that annual exit rate $\bar{k}$ is small in reality, 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 (19)–(20). We then take a log-linearization of equation (15) and take the full derivative around $r_m = 0$:

$$\begin{aligned} d\hat{l}_m &= -\phi_L \left(\delta + \frac{1}{\sigma-1}\bar{\kappa}\delta_\kappa\right) dr_m + \frac{\phi_L}{\sigma-1} d\hat{N}_m \\ &= -\phi_L \left(\delta + \frac{1}{\sigma-1}\bar{\kappa}\delta_\kappa\right) dr_m + \frac{\phi_L}{\sigma-1}\left(d\hat{\Lambda}_m + d\hat{l}_m\right) \\ &= -\phi_L \left(\delta + \frac{1}{\sigma-1}\bar{\kappa}\delta_\kappa\right) dr_m + \frac{\phi_L}{\sigma-1}\left(\left(\phi_M(1+1/\phi_L)+1\right) d\hat{l}_m - \phi_M \eta dr_m\right). \end{aligned} \tag{B.11}$$

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.11, we can solve $d\hat{l}_m$ as an equation of dr_m in equation (17).

Finally, from equation (14) and the damage equation of flooding, we obtain the average output:

$$\mathbb{E}Y_m \propto \sum_s \Pr(s) A_m(s) N_m(s)^{\frac{1}{\sigma-1}} L_m. \tag{B.12}$$

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

$$d\widehat{\mathbb{E}Y}_m = -\delta dr_m + d\hat{L}_m + \frac{1}{\sigma-1} d\widehat{\mathbb{E}N}_m. \tag{B.13}$$

Therefore, we obtain equation (21).

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,

$$Y_m^j(s) = \left(\sum_n \int_{\Omega_{nm}^j(s)} y(v,s)^{\frac{\sigma-1}{\sigma}} dv\right)^{\frac{\sigma}{\sigma-1}} \tag{B.14}$$

where $\Omega^j_{nm}(s)$ is the set of firms that trade from origin n in state s. For the nontradable sector that does not source from other regions, $\Omega^{NT}_{nm}(s) = \emptyset \; \forall \; n \neq m$. 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.[32] We calibrate γ to match the elasticity of good flows with regard to distance estimated from the Commodity Flow Survey (Allen and Arkolakis, 2014).[33] We recalibrate all internally calibrated parameters following the procedure in Section 5.2.

B.5 Capital and Housing

We now extend the production function in region m to allow for capital and structures (housing):

$$y_m(s) = A_m(s) \left[(l^d_m(s))^\beta (k^d_m(s))^{1-\beta} \right]^{1-\theta} h^d_m(s)^\theta \tag{B.15}$$

where θ is the share of costs spent on housing. The parameters $\beta(1-\theta)$ and $(1-\beta)(1-\theta)$ are the cost shares of labor and capital in the production, respectively. We also modify the worker's utility to incorporate housing:

$$\begin{aligned} U_m(s) &= v_m B_m(s) \left(c_m(s)^{1-\zeta} h_m(s)^\zeta l_m - \psi_m \frac{l_m^{1+1/\phi_L}}{1+1/\phi_L} \right), \\ &\text{s.t. } P_m(s) c_m(s) + P_{m,h}(s) h_m(s) \leq W_m(s). \end{aligned} \tag{B.16}$$

where $h_m(s)$ is the individual's demand for housing per unit of labor and $P_{m,h}(s)$ is the price per unit of housing. ζ is the share of housing costs in individuals' expenditures.

We consider that capital can be rented at the real return R from the global market. We model housing supply following Serrato and Zidar (2016): housing is supplied locally at an amount $H_m(s) = D_m(P_{m,h}(s))^\psi$ in each region, whereas the elasticity ψ captures the

[32]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.

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

responses of housing supply to housing price. To close the model, we assume that both capital income and housing income are spent on final goods in the local area. In the recalibration, we obtain the housing share in the U.S. production $\theta = 0.06$ from Caselli and Coleman (2001) and $\beta = 2/3$ such that the labor share in the total income is roughly two thirds. We consider $\zeta = 0.3$ for the share of housing costs in individuals' expenditures. We set $\psi = 3.1$ according to Serrato and Zidar (2016)'s estimate and region-specific $\{D_m\}$ such that the amount of housing supply in each region is proportional to its land areas in the calibrated economy. We set $R = 0.08$ according to the real internal rate of return in the U.S. from the Penn World Table. We recalibrate all internally calibrated parameters following the procedure in Section 5.2.

B.6 Heterogeneity in Firm Productivity

In our baseline model, we assumed homogeneity among firms in each location. We now introduce a model extension in which firms exhibit heterogeneous productivity levels, with smaller firms being more susceptible to flood shocks.

We follow the methods of Melitz (2003) and Chaney (2008) to model the firm sector in each region. Assuming that a firm entering region m draws an idiosyncratic productivity z from a Pareto distribution $F(z) = 1 - z^{-\theta}$, we can modify the production function in equation (5) as follows:

$$y_m(s) = A_m(s) z \, l_m^d(s). \tag{B.17}$$

The profits of the firm, as shown in equation (6), can be adjusted as follows (with dependence on productivity in this instance):

$$\pi_m(z, s) = \frac{1}{\sigma} \left(\tilde{\sigma} \frac{W_m(s)}{A_m(s) z} \right)^{1-\sigma} P_m(s)^{\sigma} Y_m(s). \tag{B.18}$$

Besides entry costs, we assume that firms must also employ $f_m^o(s)$ units of labor to actively produce in region m, accounting for some overhead expenses. Specifically, we assume $f_m^o(s) = \bar{f}_m^o \exp(\delta_f \xi_m(s))$, where $\delta_f > 0$ indicates that fixed operational costs can be higher in the event of a flood. A firm will actively produce if and only if $\pi_m(z, s) \geq f_m^o(s)$. In contrast to our baseline model with exogenous exits, this framework implies that only unproductive (small) firms will discontinue operations due to their reluctance to bear the fixed operational costs.

The free entry condition in equation (7) can be adjusted as follows:

$$\sum_s \Pr(s) W_m(s) \left[f_m + f_m^o(s) \int \mathcal{I}_{\{\pi_m(z,s) \geq f_m^o(s)\}} dF(z) \right] = \sum_s \Pr(s) \int \mathcal{I}_{\{\pi_m(z,s) \geq f_m^o(s)\}} \pi_m(z,s) dF(z). \tag{B.19}$$

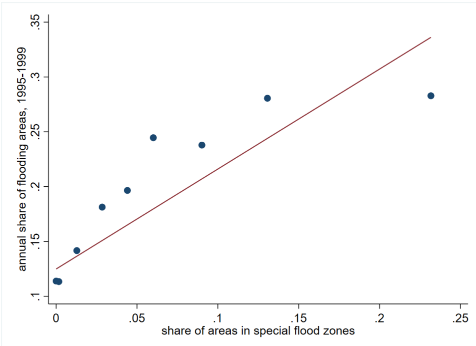
In this context, $\mathcal{I}_{\{\pi_m(z,s) \geq f_m^o(s)\}}$ functions as an indicator variable signifying whether a firm is actively producing or not. The left-hand side includes the total expected costs for a potential entrant, consisting of both entry costs and operational costs associated with active operation. On the other hand, the right-hand side depicts the expected profits generated by a potential entrant in an actively producing state. At equilibrium, free entry ensures that the total expected costs are equal to the expected profits for a potential entrant.

In the recalibration process, we assign the shape parameter of the firm productivity distribution as $\theta = 4.5$, which is a widely accepted value in the literature (Simonovska and Waugh, 2014). We select $\bar{f}_m^o$ and δ_f for each region to ensure that the annual exit rate is 0.08 in every location, and floods lead to a 0.3% increase in exits, aligning with our baseline calibration. We recalibrate all other internally calibrated parameters following the procedure in Section 5.2.

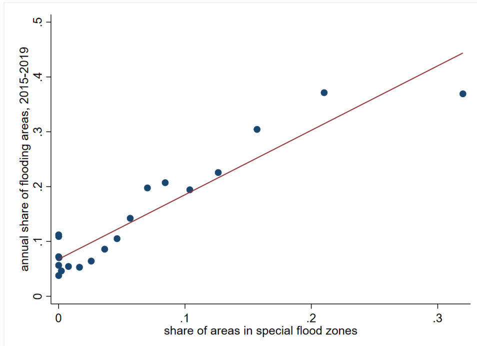
C Quantitative Analyses: Additional Results

C.1 Special Flood Zones and Actual Flood Risk

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

Notes: We group counties into 20 bins (fewer for 1998 due to a lot of zeros) ranked by the share of land in flood zones.

C.2 Additional Tables

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 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.