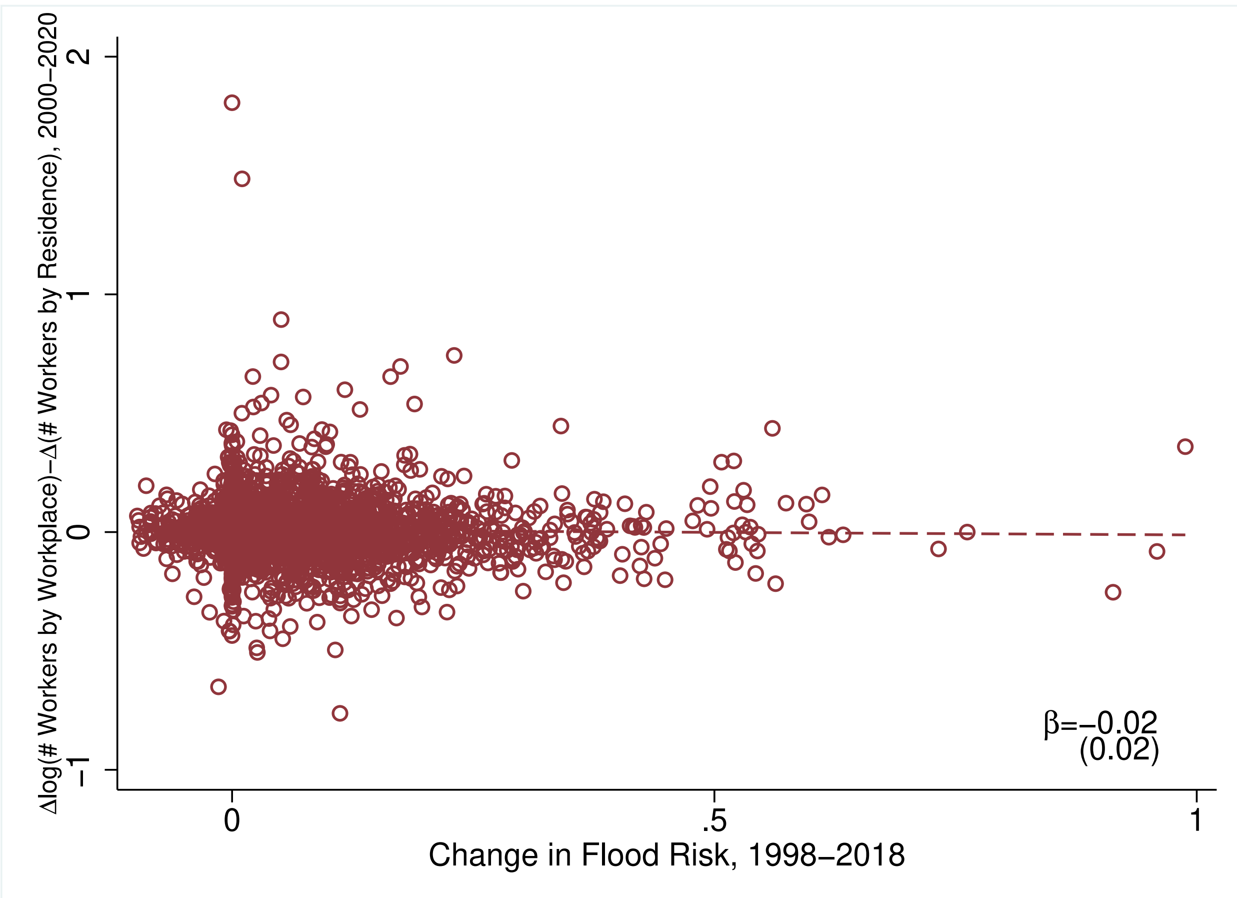
Supplemental Appendix: "Expecting Floods: Firm Entry, Employment, and Aggregate Implications" (Ruixue Jia, Xiao Ma, Victoria Wenxin Xie)

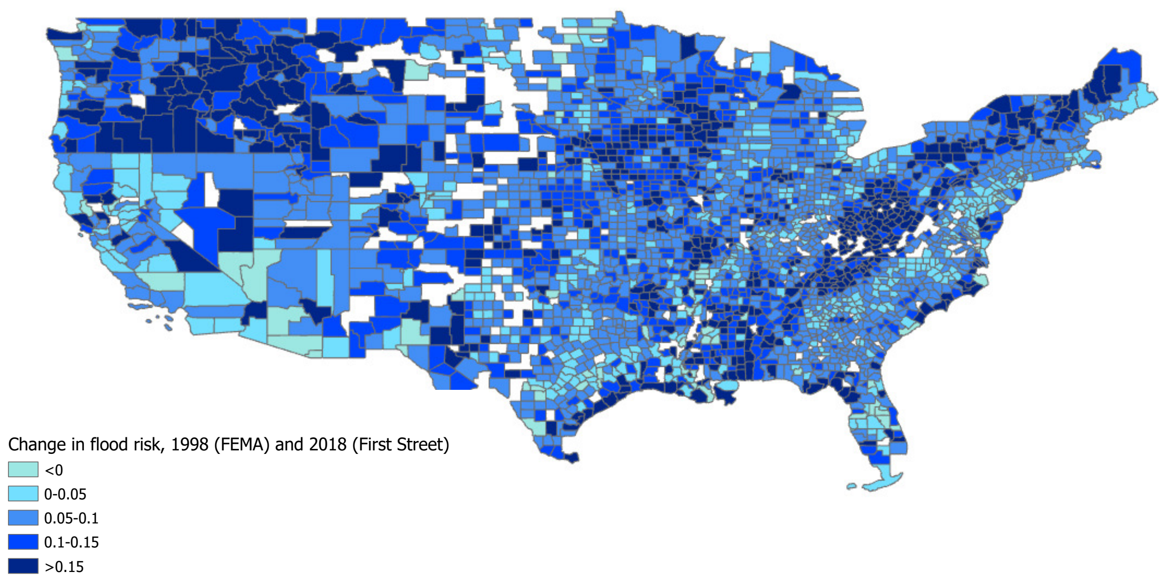
A Reduced-form Evidence: Additional Results

Figure A.1: Log Changes in Number of Workers by Workplace Relative to Number of Workers by Residence, 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
	(1.38)	(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		36.15	0.31
	(0.15)	(0.02)		(167.02)	(0.44)
Year = 2018	0.16	0.50	26.16	59.53	5.09
	(0.12)	(0.02)	(10.83)	(361.50)	(3.13)

Panel C: Independent Variables

	(1) Flood Risk	(2) Flood Share[b]
Year = 1998	0.06	0.07
	(0.11)	(0.24)
Year = 2018	0.12	0.26
	(0.13)	(0.42)

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 2001–2018 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)	(2)	(3)	(4)	(5)
	log(Entry)	log(Exit)	log(Employment)	log(Population)	log(Output)
Flood Risk	-0.341**	-0.208	-0.327***	-0.225**	-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 $\text{Risk}_{i,t}$, 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	-0.082	0.026	-0.091	-0.023
	(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 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. 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	-0.186**	-0.133*	-0.231***	-0.127***	-0.288***
	(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: 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.7: 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

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, $\prod_{n\neq m} G_n\left(\frac{v_m x_m}{x_n}\right)$,[32]

[32] 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:

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

$\Gamma(\cdot)$ 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.[33] We calibrate γ to match the elasticity of good flows with regard to distance estimated from the Commodity Flow Survey (Allen and Arkolakis, 2014).[34] 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

[33]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.

[34]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:

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

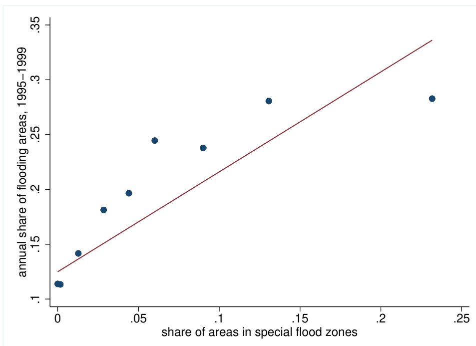
In this context, $\mathcal{I}_{\{\pi_m(z,s) \geq f_m^o(s)\}}$ functions as an indicator variable signifying whether a firm is actively producing or not. The left-hand side includes the total expected costs for a potential entrant, consisting of both entry costs and operational costs associated with active 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.

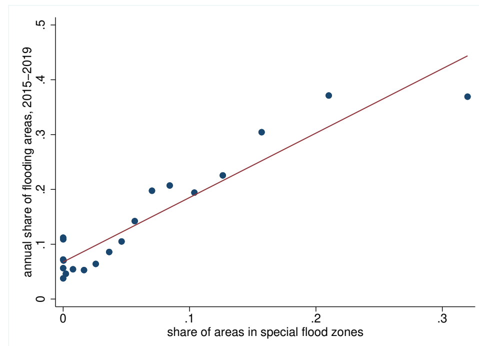
C Quantitative Analyses: Additional Results

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.