Adjusting to Rain Before It Falls

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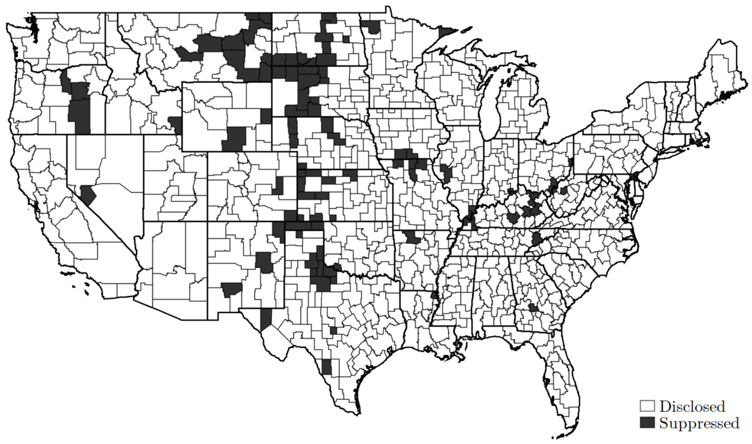
Appendix for online publication

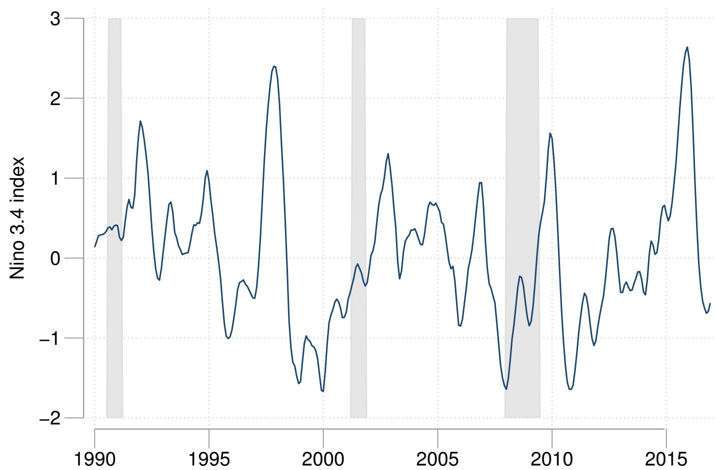
A Supplementary figures and tables

Figure A1: Commuting Zones Where Construction Employment is Disclosed



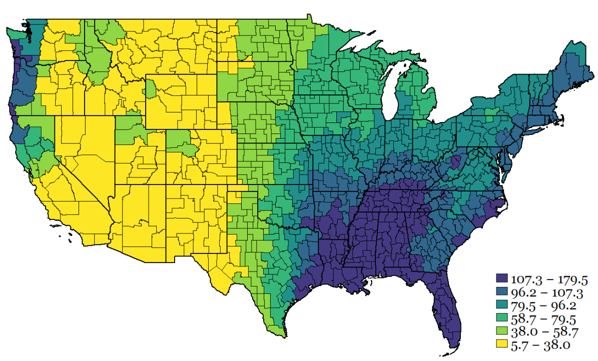
Notes: The map shows commuting zones in the continental U.S. where construction employment is disclosed (white) versus suppressed (black) for all months in our sample.

Figure A2: ENSO Temperature Anomalies

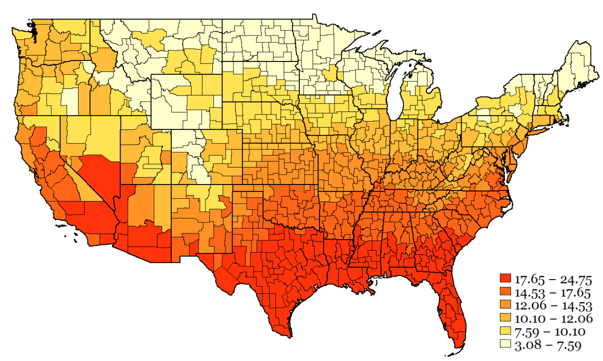


Notes: The figure shows monthly average temperature anomalies in the equatorial Pacific Ocean as measured by the Niño 3.4 index. Gray bars are NBER recession dates.

Figure A3: CZ-average rainfall and temperature over 1990 to 2016 period



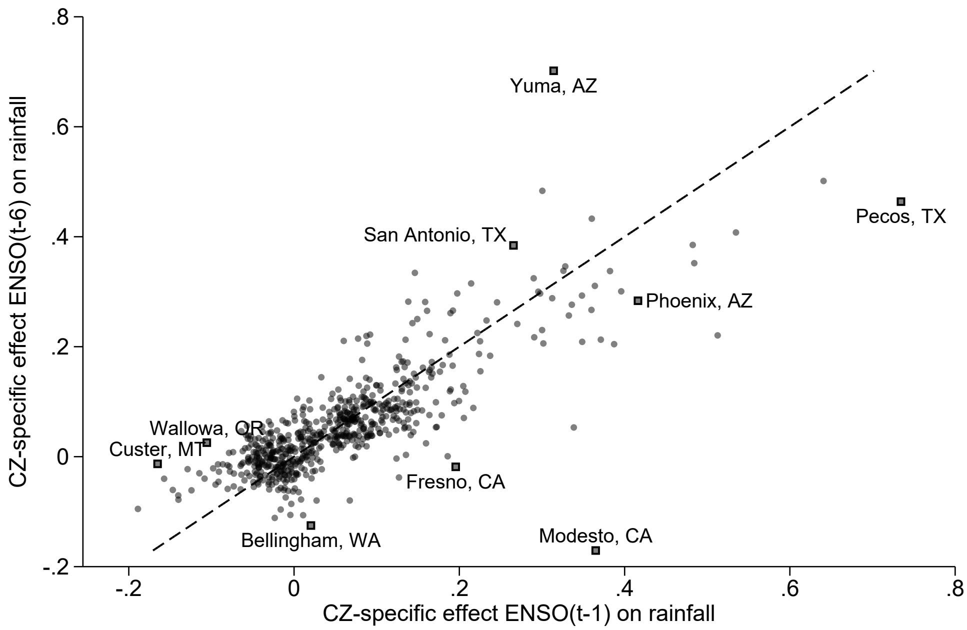
(a) Pop. weighted precipitation



(b) Pop. weighted avg. temperature

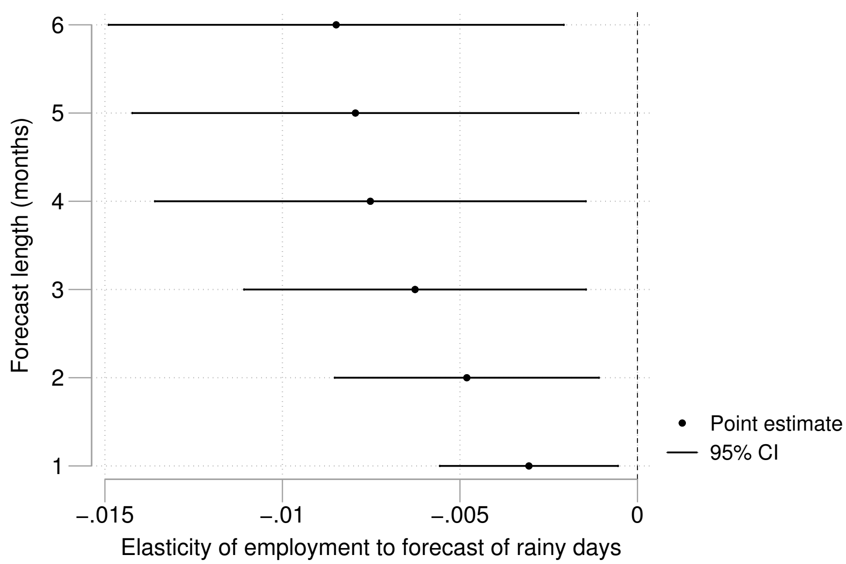
Panel (a) shows the time series average across the full sample (1990 to 2016) of population weighted monthly total precipitation (in mm) in each commuting zone. Panel (b) shows the population-weighted average temperature (in °C) for each commuting zone over the same period.

Figure A4: Comparison of First-stage Coefficients: $\ell = 1$ and $\ell = 6$



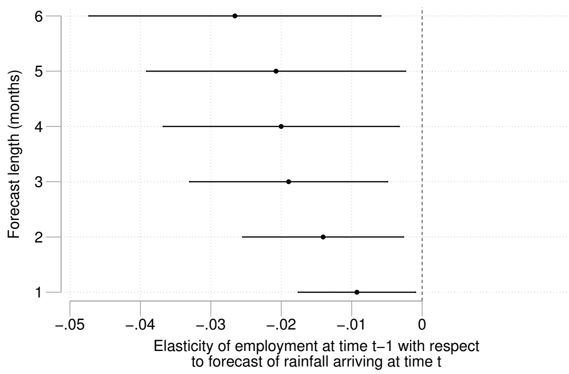
Notes: The figure shows coefficient estimates from Equation (1) for 1 and 6-month ahead predictions of the rainfall using ENSO. Example locations where the predictions at the two horizons differ substantially are labelled. The dashed line is a 45° line.

Figure A5: Main Results Using Rainy Days

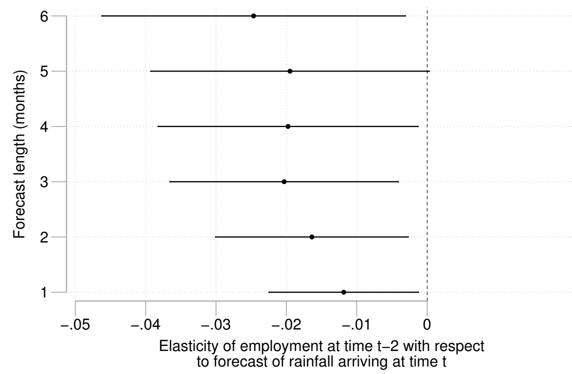


Notes: The figure shows coefficient estimates from Equation (2) for rainfall predicted 1 to 6 months ahead. Predictions are based on CZ-specific responses to changes in the ENSO. In our primary specification (see Table 2), the core independent variable is the log number of millimeters of precipitation in the month. In this specification, the core independent variable is instead the number of days in the month with positive precipitation.

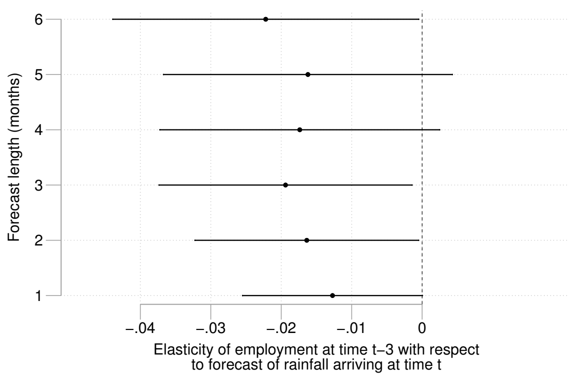
Figure A6: Effect of Rainfall Forecasts on Employment Prior to the Arrival of the Rain Shock



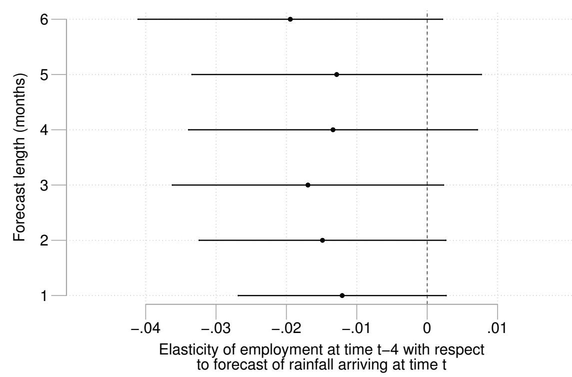
(a) $h = 1$



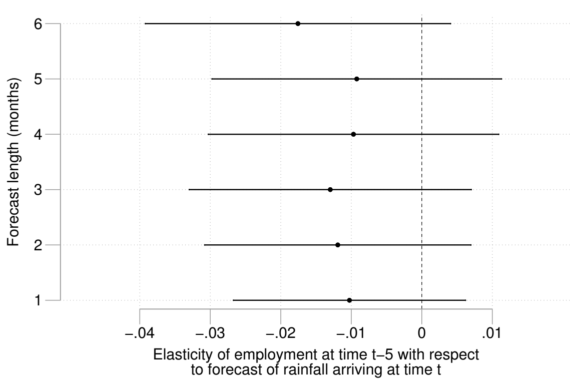
(b) $h = 2$



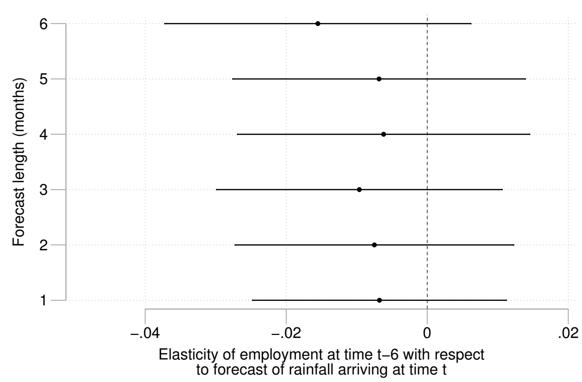
(c) $h = 3$



(d) $h = 4$



(e) $h = 5$



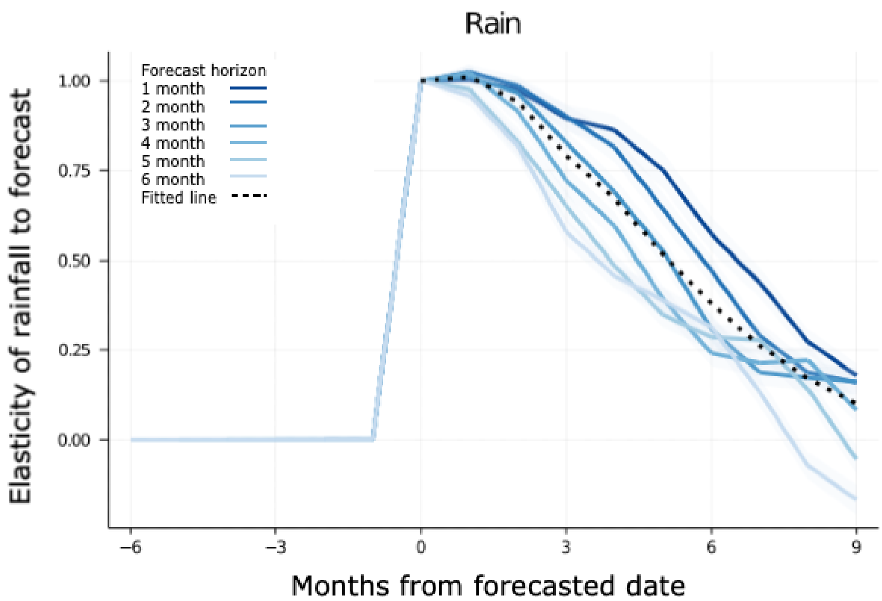
(f) $h = 6$

Notes: The figure shows coefficient estimates from Equation (2) for rainfall predicted 1 to 6 months ahead. Predictions are based on CZ-specific responses to changes in the ENSO. The dependent variable is log employment measured h months before the rain was forecast to arrive. The bars are 95% confidence intervals.

B Model and Calibration

B.1 Calibration

Figure A7: Fit of AR(5) Rain Process to Estimate Persistence of Rain Shock



Notes: The figure shows coefficient estimates for the impact of news about rain on realized rain by forecast horizon (blue lines), as well as the fit of an AR(5) process to these estimates (dashed black line). The different colors of the blue lines indicate the horizon of the forecast (1 to 6 months ahead), with the darker colors indicating shorter horizons and lighter colors indicating longer horizons. The estimates of the response of rain to the forecasts shows the empirical persistence of rainfall in response to the news shocks we use for identification. For calibrating the model, we minimize the distance between the estimates (pooling across forecast horizons) and the prediction from an AR(5) process, using standard errors as weights.

We use input-output tables from BEA and employment transition probabilities from the CPS to calibrate the model at the 2-digit NAICS level. Rather than reporting the full tables, we report aggregated values below to highlight the overall structure of the economy.

Table A1: Calibration of Scale of Rainfall Shock: Effect of Surprise Rainfall on Quarterly Earnings

	Log wage bill
$\widehat{\ln(Rain)}_t^0$	-.038**
	(.018)
N	71,443

Notes: ** $p < .05$. Table displays the estimated elasticity of compensation to surprise rainfall at time t. The data are quarterly aggregates of the monthly QCEW data used to estimate results in Table 2. Standard errors clustered at the CZ level are in parentheses. The regression includes the 6-month-ahead forecast of rainfall to isolate the surprise component of rainfall, time fixed effects, CZ fixed effects, CZ-by-quarter-of-year fixed effects, 1 year of lagged rainfall, and 1 year of lagged temperature.

Table A2: Calibration of Non-Sector-Specific Parameters

Parameter	Value	Source/Target
r	$1.02^{1/12} - 1$	2% APR
β	$1.02^{-1/12}$	2% APR
μ^S	.171	Housing to consumption expenditure (BEA use IO table)
δ^S	0.00154	Housing investment to housing expenditure (BEA use IO table)
δ^K	0.00170	Capital investment to payments to capital (BEA use IO table)
s	0.066	Share of workers in same sector with a new employer (CPS)

Notes: Payments to capital are inferred as value added net of labor compensation.

Table A3: Mapping of NAICS Codes to Aggregate Sector Names for Calibration Tables

NAICS Code	Sector Name	Aggregate Name
11	Agriculture	Traded
21	Mining	Traded
22	Utilities	Services
23	Construction	Construction
31-33	Manufacturing	Traded
42	Wholesale Trade	Services
44-45	Retail Trade	Traded
48-49	Transportation and Warehousing	Traded
51	Information	Traded
52	Finance and Insurance	Services
53	Real Estate	Real Estate
54-55	Prof., Sci., and Tech. Services	Services
56	Admin., Support, and Waste Management	Services
61	Education	Services
62	Healthcare and Social Assistance	Services
71	Arts, Ent., and Rec.	Services
72	Accommod. and Food Services	Services
81	Other Non-Public Services	Services

Notes: The table shows the mapping between 2-digit NAICS codes (and the associated industry name in Column 2) and the aggregate sector name we use for display in the calibration tables below. Note that the model is fit to the disaggregated (2-digit sector-level) data but we report aggregated sectors for legibility.

Table A4: Commodity Data and Calibrated Parameters

	Share of Total	Expenditure Shares				Sector i's Share of Revenue			
		μ_j^C	μ_j^S	μ_j^K	μ_j^G	Φ_{ij}			
Commodity						Const.	R.E.	Serv.	Traded
Construction	0.0616	0.0039	0.7709	0.1788	0.1015	0.9694	0.0012	0.0091	0.0204
Real Estate	0.0505	0.0207	0.1255	0.0032	0.0	0.0	0.883	0.018	0.099
Services	0.2339	0.4869	0.0143	0.0284	0.0	0.0	0.0012	0.984	0.0148
Traded	0.6539	0.481	0.0893	0.7896	0.1113	0.0002	0.0001	0.0052	0.9946
Government	0.0001	0.0076	0.0	0.0	0.7872	0.0	0.0	0.0	1.0

Notes: Data is from BEA final use table. NAICS codes associated with the listed sector names are given in Table A3.

Table A5: Sector Data and Calibrated Parameters

Sector	Share of GDP	Labor Share $1-\alpha_i$	Materials Share γ_i	Commodity j's Share of Materials Γ_{ij}/γ_i				
				Const.	R.E.	Serv.	Traded	Gov't
Construction	0.0603	0.635	0.483	0.0003	0.049	0.1453	0.8053	0.0
Real Estate	0.0386	0.2201	0.5609	0.0602	0.1657	0.2861	0.4837	0.0043
Services	0.29	0.6826	0.3674	0.0048	0.1424	0.1836	0.6538	0.0154
Traded	0.611	0.5777	0.5256	0.0061	0.0549	0.081	0.8504	0.0076

Notes: Data is from BEA final use and IO tables. The labor share refers to the share of value-added paid to as labor compensation. Materials share refers to the share of materials costs in total revenue. NAICS codes associated with the listed commodity/sector names are given in Table A3.

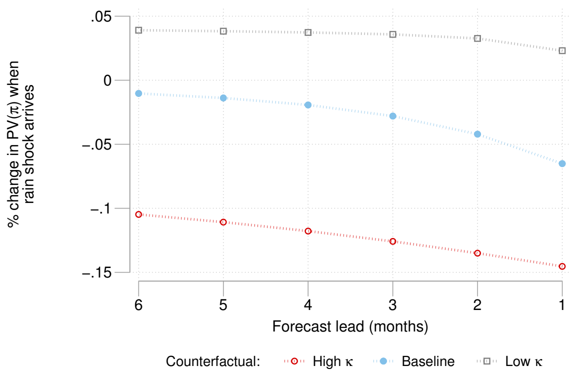
Table A6: Employment Statistics (Calibration target for $\omega_{ii'}$)

Sector	Share of Total	Percent Transitioning to Sector				
		Non-Emp.	Const.	R.E.	Serv.	Traded
Non-Employment	0.14	0.7277	0.0252	0.0046	0.1483	0.0943
Construction	0.0597	0.0597	0.904	0.0014	0.011	0.0239
Real Estate	0.015	0.0448	0.0052	0.9148	0.0163	0.0189
Services	0.4101	0.0496	0.0017	0.0006	0.9329	0.0151
Traded	0.3752	0.0362	0.0038	0.0008	0.0156	0.9437

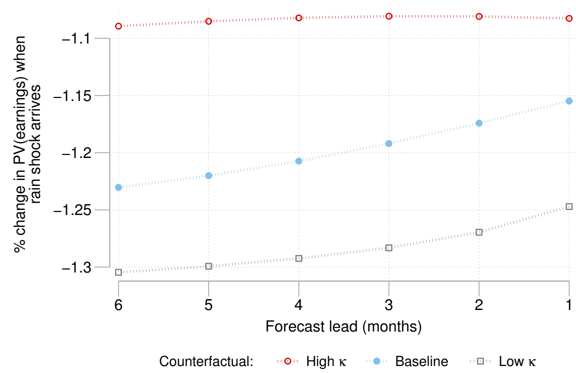
Notes: The second column reports total share of workers by sector (industries or non-employment, CPS). The entries on the right show the share of these workers moving from that sector to each other sector per month in the current population survey (CPS). NAICS codes associated with the listed sector names are given in Table A3.

C Additional Results Figures

Figure A8: Present Value of Profit and Labor Value When Rain Arrives



(a) Present Value of Profit

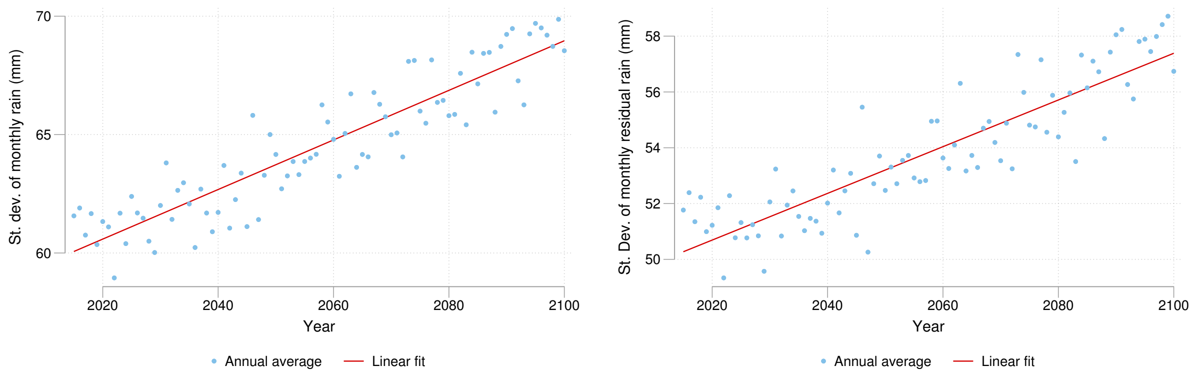


(b) Present Value of Earnings

Notes: The figure shows the present value of profit for firms (Panel A8a) and present value of earnings for workers (Panel A8b) as a function of the forecast horizon and three different values of the firm-side adjustment cost parameter, κ: high (red with hollow circles), baseline (blue with filled circles), and low (gray with hollow squares) adjustment costs. All values are calculated at the time when the rain shock arrives (time t in Equation (2)).

D Climate Projections

Figure A9: Projected monthly rainfall standard deviation for the continental U.S.



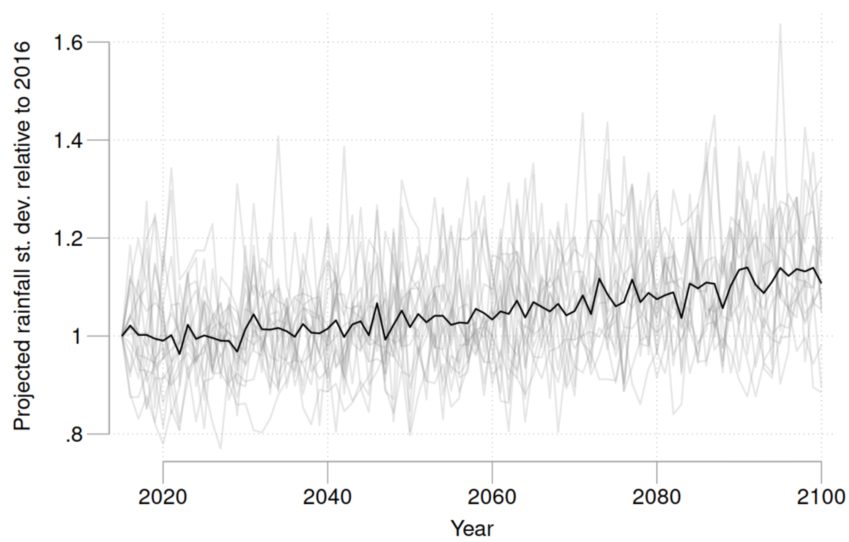
(a) Raw std. dev.

(b) Residual std. dev.

Panel (a) shows the projected standard deviation of monthly rainfall (in mm) each year from the present until 2100 in CMIP6 SSP5-8.5 (O'Neill et al., 2016). Each point is calculated by taking the month-to-month standard deviation of rainfall for each grid point in the CMIP6 projections then averaging those values across the continental U.S. The raw standard deviation is debaised to match the sample average from our estimation sample (by adding 2.04 to the projection values). Panel (b) shows the same standard deviations but where the monthly rainfall in each grid point is first residualized on month, year, grid point, and climate model fixed effects then the standard deviation is calculated.

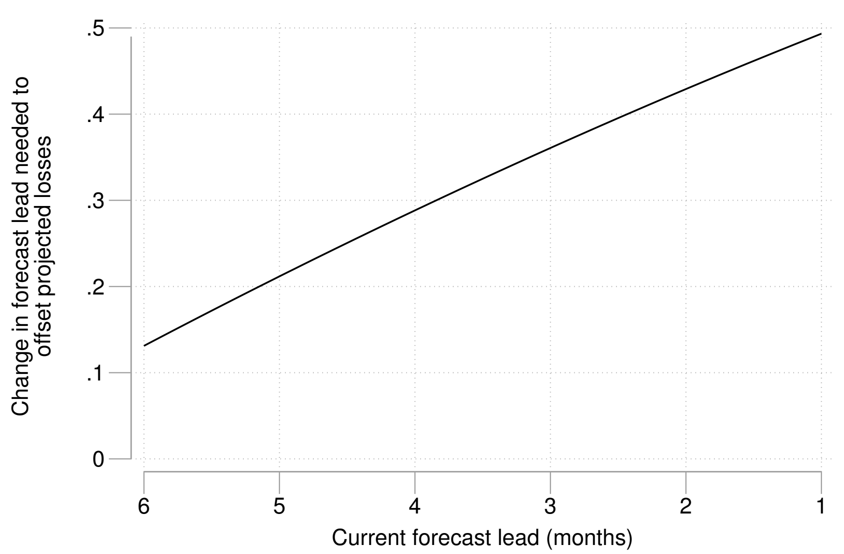
E Model Robustness Checks

Figure A10: Projected change in monthly rainfall standard deviation for the continental U.S.



The figure shows the projected growth in the standard deviation of monthly rainfall (in mm) each year from the present until 2100 in CMIP6 SSP5-8.5 (O'Neill et al., 2016). Each line is indexed to 1 in 2015. The gray lines are from different climate models in the CMIP database. The black line is the monthly average across models.

Figure A11: Forecast horizon improvement needed to offset projected losses



The figure shows the gain in forecasts needed to offset losses from the projected change in the standard deviation of monthly rainfall caused by climate change (shown in Figure 7) in our baseline calibration. The line is the horizontal distance between the baseline profit loss and the profit loss under the projected increase in rainfall volatility as a function of forecast horizon.

Table A7: Model Robustness Checks: Spillovers to Agriculture

		Elasticity of Agriculture Productivity to Rain			
ℓ	Baseline	$-.5\hat{\epsilon}$	$-\hat{\epsilon}$	$-2\hat{\epsilon}$	$\hat{\epsilon}$
1	−0.005554	−0.005424	−0.005294	−0.005033	−0.005814
2	−0.009629	−0.009409	−0.009189	−0.008749	−0.010069
3	−0.013771	−0.013467	−0.013164	−0.012556	−0.014379
4	−0.017659	−0.017286	−0.016913	−0.016168	−0.018404
5	−0.021133	−0.020709	−0.020285	−0.019437	−0.021981
6	−0.024141	−0.023682	−0.023223	−0.022306	−0.025058

Notes: The values reported in the table are model predictions for the elasticity of construction sector employment to anticipated rain by length of forecast ($\ell = 1, \ldots, 6$) while allowing rain to impact productivity in agriculture, in addition to construction. The first column shows when rain does not impact agriculture (corresponding to the "baseline" values in Figure 3). The following columns show predictions when we set the elasticity of agriculture productivity to some multiple of our estimated elasticity for construction.

Table A8: Model Robustness Checks: Heterogeneity in κ

		Heterogenous κ		
ℓ	Baseline	$\frac{\partial \ln \kappa_i}{\partial \ln W_i} = .1$	$\frac{\partial \ln \kappa}{\partial \ln W_i} = 1$	$\kappa_i = 0$ for $i \neq$ Const.
1	−0.005554	−0.005552	−0.005536	−0.00564
2	−0.009629	−0.009626	−0.009593	−0.009781
3	−0.013771	−0.013767	−0.013714	−0.013984
4	−0.017659	−0.017652	−0.017579	−0.01792
5	−0.021133	−0.021125	−0.021033	−0.021426
6	−0.024141	−0.024131	−0.024022	−0.02445

Notes: The values reported in the table are model predictions for the elasticity of construction sector employment to anticipated rain by length of forecast ($\ell = 1, \ldots, 6$) while introducing heterogeneity in κ across industries. The first column shows the predictions when κ is common across industries and equal to our estimate of 65.5 (corresponding to the "baseline" values in Figure 3). The following columns show predictions after adding heterogeneity in κ across industries (keeping the value in construction constant). The second and third columns introduce heterogeneity by allowing κ to be a log-linear function of steady state wages. The second sets the elasticity of κ to wages to .1 (matching the estimate in Muehlemann and Pfeifer (2016)), while the third increases this elasticity by an order of magnitude to 1. The final column shows predictions when there are no adjustment costs in industries other than construction.