Adjusting to Rain Before It Falls

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Abstract

Unchecked climate change will cause precipitation volatility to increase around the world, leading to economic damages in the face of adjustment costs. We estimate these damages for construction—an economically important, climate exposed industry. Empirically, employment falls in response to forecasted rainfall and more so as the forecast horizon increases. This pattern allows for identification of labor adjustment costs via a multi-sector model of local labor markets calibrated to our estimates. When rainfall is anticipatable 1 month ahead, construction firms pay 10% of monthly profit to adjust. They pay less than 1% for rainfall anticipatable 6 months ahead. Without further adaptation or forecast improvements, increased rainfall volatility due to climate change is projected to lead to more costly adjustment. (JEL:D83,J21,Q51)

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1 Introduction

Beyond simply warming the earth, climate change will have profound effects on the complete distribution of weather. While much of the literature has examined the economic consequences of changes in average weather (including rising temperatures and sea levels), in this paper we consider economic effects of changes in the *volatility* of weather. We focus on productivity interruptions caused by rainfall, show that firms incur serious costs from the types of rainfall shocks that climate change makes more common, and study the extent to which scientific advances in forecasting and attentive planning by managers can offset these costs.

We focus on the construction sector, a large and economically important industry that is highly exposed to the climate. Construction constitutes a five times larger share of GDP in the U.S. than the more widely studied forestry, fishing, and agriculture sector (BEA, 2019).[1] Beyond simply its size, construction is central to the economy, supplying essential inputs to virtually all other industries and using materials produced by many other sectors. At the same time, weather directly impacts construction. Data from the American Time Use Survey shows that only agricultural workers spend more time outside than construction workers. Combined with the importance of construction to the overall economy, month-to-month disruptions due to weather can be an important source of economic costs.

Despite its economic importance and potential climate vulnerability, construction has not been the focus of research in the climate economics literature.[2] This literature has focused either on the costs associated with equilibrium consequences of gradual changes in average temperature and precipitation or on the acute effects of realized weather shocks, both of which have first order effects on sectors like agriculture and energy.[3] In contrast, we focus on the costs regularly paid due to *ex ante* adjustment to weather events, and we use evidence from the construction sector to infer the increase in these costs that will occur after climate

[1]This multiple is not an outlier. According to UNECE (2019), the construction industry is 9 times larger than agriculture in the U.K. and 6 times larger in Germany. Even in more heavily agriculturally reliant countries like Spain and Italy, construction is more than twice the size of agriculture in terms of its contribution to GDP.

[2]For the few studies that do look at construction, the emphasis is often on potential job growth as other sectors comply with climate policy or adapt to a changing climate. See Fankhaeser et al. (2008), for example. Some research studies sectoral effects of weather and climate change. Graff Zivin and Neidell (2014) estimate the effects of temperature on intensive-margin labor supply in construction and other climate-exposed industries. Jain et al. (2020) investigate the effects of temperature on economic production for multiple sectors in India including construction. More studies have focused on agriculture, a sector we abstract from in this paper. As discussed below, rainfall has offsetting positive and negative effects on agricultural, and the agricultural labor market in the U.S. is largely segmented from from other labor markets (Taylor, 2010).

[3]Zhang et al. (2017) points out that a wide range of climate variables—not just temperature and precipitation—will likely have important effects on agriculture.

change has shifted weather patterns.

Climate change will increase rainfall volatility as warmer air masses hold and then suddenly release larger volumes of water (Pendergrass et al., 2017). This effect is often summarized by the saying that as a result of climate change, "wet regions get wetter and dry regions drier" (Held and Soden, 2006). Climate projections also show that within locations, the time series volatility will increase (O'Neill et al., 2016).[4] Consistent with a large body of evidence on the costs of volatility in conditions like product demand or supply chains, we show that productivity volatility caused by rainfall shocks is an important—but rarely quantified—cost of climate change.[5]

We empirically identify adjustment costs in the construction industry by estimating employment responses to more or less forecastable rainfall. Our primary focus is on how medium-range forecasts of weather conditions in the coming six months affect the dynamics of employment responses to rainfall. We combine data on construction employment in commuting zones (CZs) across the United States over the last three decades with: *i*) information on monthly rainfall and *ii*) climate variation that can be used to forecast rainfall month-to-month. These data allow us to estimate employment responses to exogenous news shocks about future rainfall. Our identification strategy exploits rich variation in weather patterns across the U.S. to identify separate employment responses to forecasts available at different horizons (ranging from one month to six months in advance). To help validate our empirical approach, we provide extensive discussion of the ways in which rainfall is a serious and well-recognized challenge in construction sector, construction firms actively monitor the types of medium-range forecasts we rely on for identification, and commonly used contracts shift weather risk from site owners onto construction firms.

We find that the elasticity of construction employment with respect to rainfall is five times larger when that rainfall could be predicted 6 months in advance compared to when it could only be predicted 1 month in advance. In other words, an identical rainfall "shock" generates a significantly larger employment response when it is predictable further in advance. This empirical reduced form finding cannot be reconciled with simple, frictionless, static models of labor input, which is important partly because these models remain the norm for analyzing economic effects of climate change.

To interpret the reduced form effects, we model a multi-sector, open-economy with both

[4]Over the last 30 years, month-to-month variance in rainfall has increased by about 5% in the U.S. CMIP6 projections indicate that variance will go up another 10 to 15% by the end of the century under unmitigated warming.

[5]The effects of temperature variability have been studied in papers such as Lemoine and Kapnick (2016). Studies of rainfall variability are more rare even though increases in rainfall variability are consistent projection from climate models. Fishman (2016) evaluates the effects of rainfall variability on agriculture, finding that climate-change-driven increases in rainfall volatility (leading to a higher probability of dry days) will offset the benefit of increasing total rainfall.

demand-side and supply-side adjustment costs. We calibrate the model to match the estimated employment dynamics. Unlike the benchmark models widely used for climate economics, our model creates a channel by which volatile productivity can harm firms (because they wish to adjust their input demands but must face costs of doing so). We use this model to understand how productivity and output are affected by rainfall shocks, how the burden of these shocks is shared between workers and firms, and the extent to which firms are able to adjust employment to avoid the costs of the shock. Throughout the counterfactuals, we pay special attention to how the results would change if firm-side adjustment costs fall (for instance, because firms write more flexible employment contracts that allow greater responsiveness to shocks) or the forecast horizon for the rainfall fluctuation increases (for instance, because managers increasingly use better scientific models).

In the benchmark calibration, we find that rainfall shocks reduce firm profits and harm workers' productivity. Faced with adjustment costs, firms and workers hit by surprise rainfall events suffer substantially. With longer horizon forecasts, the effect is different. A firm that is able to forecast the shock six months in advance can offset 86% of the profit loss that occurs in the counterfactual world where it was only able to forecast the shock one month in advance. But enhanced flexibility for the firm creates a real policy trade-off. Firms largely offset the effects of the productivity shock by passing the costs onto workers, leaving workers to bear a larger part of the burden of the shock.

The firms do need to pay a cost to engage in this adjustment. There is a direct cost stemming from changes to the labor force and the adjustment costs we estimate. These costs are always weakly positive, and they occur whether the rainfall shocks help or hurt productivity. The level of adjustment cost also determines how willing the firm is to engage in *ex ante* labor adjustment in order to reduce damages when the shock arrives. In our baseline calibration, we show that adjustment costs are high enough to lead to non-trivial adaptation costs for firms, but low enough to make firms want to engage in substantial adjustment—particularly if they have enough advance notice before the shock arrives.

If rainfall gets more volatile in the future—as climate projections currently indicate it will—then the adjustment costs we estimate will translate into extra damage for the economy. This is a source of climate damage that is currently omitted from economic assessments of climate change. Conditional on a rainfall shock occurring, higher volatility means that a rainfall shock will have a higher probability of being larger in magnitude. In the absence of adaptation, larger shocks will cause bigger losses in productivity and profit for firms. Our estimates, however, show that firms can offset some of those losses by planning further ahead. Given the projected 10 to 15% increase in rainfall volatility by the end of the century, a firm would require up to a half-month further ahead forecast to be left no worse off.

These results thus can serve as a warning about future climate damages while also pointing to two avenues firms can explore to reduce their risks. Construction managers know that their bottom line is affected by weather and have substantial experience planning for adverse weather (Trauner et al., 2018). If managers can further improve the quality and accuracy of their plans, then they can reduce the losses they will take if bad weather arrives. In-house project managers, weather risk consulting firms, and professional forecasters might all be able to aid in this effort. Improvements in forecasting at the horizons we study here, however, are challenging (Toth and Buizza, 2019). And as the results on workers show, forecast improvements come with the potential for increasing inequity in the incidence of climate damages. Second, managers can potentially invest in ways to reduce the adjustment costs they face. The construction industry already routinely uses seasonal contracts to manage the workforce during the winter (Krane and Wascher, 1999, Organization, 2016). A contract for shorter-run weather shocks that resembles these seasonal contracts could, for instance, reduce the costs the firm needs to pay to build back up the labor force after the shock dissipates.

Our paper provides a methodological contribution by introducing a unique empirical strategy to identify labor adjustment costs. It also draws the link between those costs and climate change. There is a nascent literature focusing on the effects of climate change on labor markets, primarily in agriculture (for instance, see Rosenzweig and Udry (2014), Colmer (2020)). The current paper shows that climate change is important for extensive margin labor adjustment in construction. Effects in construction might be particularly relevant because construction services—like seawalls; retrofits of buildings to improve heating, ventilation, and air conditioning systems; accommodation of changing patterns of urbanization—will be important components of adaptation to climate change (Fried, 2019).

At the same time, our results show that adjustment costs in the construction sector mean that an important part of the effect of climate change on the industry happen before weather realizations occur. Failing to take this forward-looking component into account can bias estimates of the effect of climate change (Shrader, 2020, Lemoine, 2021). The methodology from this paper is directly portable to other locations around the world where monthly or seasonal forecasts are available (organizations like the National Oceanic and Atmospheric Administration (NOAA) and the European Centre for Medium-Range Weather Forecasts (ECMWF) now routinely provide such forecasts globally (Scher and Messori, 2019)).

Finally, our paper investigates a novel dimension of the damage from climate change. In this paper, when we say "adjustment costs," we are referring to costs routinely paid, day to day, that arise because of a widening of the weather distribution. It is important to note that these are not adjustment costs paid when transitioning between equilibria. Instead, they are costs that are already being paid in steady state, every time rain arrives. Under projected climate change, we will simply be paying them more often. These costs are missing from existing analyses of the damages of climate change. Related to this point, as an added empirical contribution of our paper, the short-run nature of these costs mean that existing data speaks more directly to them than to costs arising from differences in long-run equilibria.

2 Related literature and background

2.1 Previous research

Volatility is central to business decisions. Volatility in either productivity or product demand has been shown to explain differences in investment behavior (Kellogg, 2014), market size and competition (Collard-Wexler, 2013), employment contracts and outsourcing decisions (Abraham and Taylor, 1996), and the "misallocation" of factors of production (Asker, Collard-Wexler, and De Loecker, 2014).[6]

Beyond its direct implications for firms' operational decisions, the importance of volatility is informative about the fundamental structure of the labor market. Models with a frictionless, perfectly competitive labor market (still the foundations of many policy analyses, including climate models) leave no room for volatility. If firms can freely adjust their labor force, as these models assume, then employment and profits depend only on the actual conditions firms are facing at any given moment. Changes in those conditions, regardless of their size, frequency, or predictability, are not important because firms can costlessly and immediately re-optimize.

It has long been understood that this is not realistic. Firms face dozens of complex costs in changing their labor pool.[7] The private sector has understood this longer than academic economists have. In his seminal 1962 paper, Walter Oi (1962) argues that non-negligible hiring and training costs mean that part of a firm's labor is a fixed cost. Oi rests this argument largely on an internal study done a decade earlier by the International Harvester Company (IHC) called "The Costs of Labor Turnover" (1951). There, IHC economists estimate that the average cost of training a new worker was \$238, or about 11% of median annual earnings at the time (\$2,200). These costs have remained remarkably persistent. Representative establishment surveys conducted today estimate that the costs of replacing

[6] The bulk of empirical studies of productivity, including those focused on volatility, treat it as a residual (i.e., excess production after accounting for inputs). The estimation challenges in this approach are substantial and well-understood (Ackerberg, Caves, and Frazer, 2015). A contribution of our paper, made possible by our context, is that we study productivity shocks using a direct measure of productivity: rainfall, which has first order effects on the ability to perform construction, as discussed below.

[7] Our focus is on the effects of increasing the *volatility of* productivity fluctuations, since this is directly linked to climate change. A separate but related issue is the effects of *uncertainty about* future productivity fluctuations. As Bloom (2009) points out, uncertainty about future productivity also has no effect in a frictionless model, but in a model with realistically calibrated adjustment costs, can have first order effects on aggregate employment and output.

an employee are 9% of average annual earnings (Dube, Freeman, and Reich, 2010).

The costs facing a firm wishing to adjust its labor pool extend beyond recruiting and training workers. A large literature on wrongful discharge regulations shows that these regulations impose firing costs. By making it more difficult for firms to dismiss workers when they need to, firing costs have been shown to reduce firms' hiring, turnover, ability to respond to shocks, and ultimately their financial value (see Serfling (2016) for a review).[8] Independent of these regulations, all U.S. firms' face direct financial costs of layoffs arising from the financing rules of the Unemployment Insurance system (Ratner, 2013).[9]

More generally, a range of diverse evidence—including the costs firms incur when they suddenly and unexpectedly lose an employee (Ginja, Karimi, and Xiao, 2020, Isen, 2013, Jäger and Heining, 2019), the value to firms of hiring through employee referral networks (Burks et al., 2015), and employers' learning about employee skills over time (Kahn and Lange, 2014)—suggests that firms cannot easily shrink or grow their workforce without costs: a firm's current workers and the potential alternatives "out there" are imperfect substitutes.[10] At a minimum, given incomplete markets and imperfect insurance for risk, a firm that is likely to suddenly cut its workforce must still compensate its workers (through higher wages) for accepting this risk, an idea which dates back to Adam Smith (1776).[11]

Against this backdrop, our core contributions are, first, to estimate the magnitude of adjustment costs in the construction sector using a novel strategy that exploits variation in whether and when rainfall-driven productivity fluctuations could have been predicted, and second, to quantify the consequences of increasing rainfall volatility driven by climate change. An advantage of our method for estimating adjustment costs is that it comprehensively

[8] A paper closely related to ours is Adhvaryu, Chari, and Sharma (2013), who study how agricultural employment responds to rainfall in India. They focus on differential responses depending on wrongful discharge laws and their implications for labor regulation. We focus on differential responses depending on whether and when that rainfall could have been predicted and the implications for rising volatility driven by climate change.

[9] While much of the literature emphasizes regulations as the source of frictions and adjustment costs, 19^{th} century manufacturing wages show evidence of imperfect competition in the labor market and firm-specific rents, even before labor regulations existed in the U.S. (Naidu and Yuchtman, 2018).

[10] One challenge facing firms is screening applicants for quality. There is growing evidence that non-cognitive skills and traits are becoming increasingly important in the labor market (Edin et al., 2017), and this matters because it is likely even more difficult to screen for these skills than for cognitive or training-based skills. Many of these non-cognitive traits are directly relevant for construction firms. For instance, construction firms need workers who are reliable and will arrive on time, who can get along with others in an inherently interactive job, and who respect and value safety practices, all of which are extremely difficult to assess during the hiring process. This increases the incentive for construction firms to keep their workers and the challenges of changing staffing levels in response to demand fluctuations.

[11] "In the greater part of manufactures, a journeyman may be pretty sure of employment almost every day of the year that he is able to work. A mason or bricklayer, on the contrary, can work neither in hard frost nor in foul weather, and his employment at all other times depends upon the occasional calls of his customers. He is liable, in consequence, to be frequently without any [employment]... The high wages of those workmen, therefore, are not so much the recompence of their skill, as the compensation for the inconstancy of their employment."

includes all types and sources of adjustment costs. Analyses of specific laws (like wrongful discharge laws (Serfling, 2016) or unemployment insurance financing (Ratner, 2013)) only capture one specific source of adjustment costs, and survey-based approaches (like Oi (1962) and Dube et al. (2010)) can easily miss important types of costs. An advantage of our application to climate change is that our estimation strategy is explicitly and directly linked to our counterfactual of interest (month-to-month volatility of rainfall), and outlines clear implications for firms and policy to respond (improving the ability to forecast future rainfall).

2.2 Industry attention to rainfall and long-range forecasts

The construction industry is a natural and important setting to estimate the effect of climate volatility—particularly from rain—on employment and productivity. Construction firms face strong incentives to pay attention to and plan for rain. Rain delays the completion of construction projects, and the costs of those delays typically fall on the construction contractor.

Rainfall makes outdoor work more hazardous by reducing visibility and increasing the risk of slipping or falling. Rain generates mud that can impede access to a work site and prevent the use of heavy machinery. It also prevents certain types of welding, electrical work, and cement pouring. Rain can even delay indoor work. For example, heavy rainfall can cause the water table to rise, delaying basement construction. Finally, construction firms in the United States are required by the Environmental Protection Agency to control rain-driven pollution effluent from work sites, requiring the diversion of labor and capital to that task (Environmental Protection Agency, 2009). One recent estimate by Ballesteros-Pérez et al. (2018) shows that weather variation delays the average construction project by 22%.

Under common contracts, construction firms bear much of the risk for weather-related delays (Trauner et al., 2018). The American Institute of Architects Form A201—a standard contract between a construction contractor and a site owner that is widely used in the U.S.—stipulates that the contractor is responsible for any rain delay that could have been "reasonably anticipated."[12] Even if a delay is caused by potentially unreasonable weather, the contractor must still bring a claim and show, as a matter of fact,[13] that the weather was more extreme than could have been expected. This finding of fact requires that the contractor record and pay attention to weather conditions during the construction project.[14]

[12] In the contract, construction firms can attempt to lengthen the contract without incurring cost under A201 §15.1.6.2, which reads: "If adverse weather conditions are the basis for a Claim for additional time, such Claim shall be documented by data substantiating that weather conditions were abnormal for the period of time, could not have been reasonably anticipated, and had an adverse effect on the scheduled construction."

[13] *A matter of fact* is a legal term for an actual occurrence, in contrast to *a matter of law* which is the purview of the judge.

[14] If not otherwise stated by contract, the presumption in the courts is that weather risk falls squarely on the contractor. Associated Engineers and Contractors v. State, 58 Haw. 322: "Moreover, the risk of

Even if a construction contractor successfully makes a claim for an extension to a delayed project, the contractor might simply avoid paying for the delay without gaining any additional recompense. Moreover, beyond the within-project costs, delays in one project can have knock-on effects of other projects that make them even more costly. Typical construction projects in the U.S. take at least 6 months from start to completion, making monthly rainfall forecasts that extend out to this horizon like the ones we study particularly relevant for the decisions by construction firms U.S. Census (2021).

Given the high cost of weather delays and the contractual need to form "reasonable" expectations about those delays, construction firms devote substantial resources to planning for weather. Bids at the beginning of jobs routinely include a monthly breakdown of expected weather delay days, and the construction project manager is expected to record actual delays relative to this schedule (Trauner et al., 2018).[15] Specialized, proprietary project management software helps review weather data before and during a project.[16]

The key implication of all this is that the construction industry pays particular attention to *long-range* weather forecasts and the El Niño/Southern Oscillation (ENSO) variation that we use in our analysis is the most important element of those. ENSO is a coupled oceanic-atmospheric phenomenon that occurs in the equatorial Pacific Ocean and is a primary driver of medium term global climate variation (Ropelewski and Halpert, 1987). El Niño events lead to higher rainfall in most (but not all) of the U.S.[17] ENSO events change weather sometimes for months thereafter, allowing forecasters to make skillful predictions of weather patterns over monthly, seasonal, and annual horizons. The ECMWF, the premier numerical weather forecasting group in the world, states that "Long term predictions [extending out to seven months] rely on aspects of Earth system variability which have long time scales (months to years) and are, to a certain extent, predictable. *The most important of these is the ENSO (El Niño Southern Oscillation) cycle.*" (emphasis ours, ECMWF (2019)). NOAA also issues seasonal weather forecasts for the U.S., again relying heavily on predictability coming from ENSO.[18] The long-range (monthly and seasonal) forecasts from NOAA's Climate Prediction Center have been available online since 1995. The project planning tools used by construction firms and discussed in the previous paragraph are proprietary and do not disclose what goes

abnormal weather is commonly held to be assumed by a construction contractor, except where provision otherwise is made in the contract or the parties are not equal in their knowledge of relevant weather data. Hardeman-Monier-Hutcherson v. United States, 458 F.2d 1364 (Ct. Cl. 1972)."

[15] These project managers make up 9% of all employment in the construction industry and hold college degrees at similar rates to the full U.S. workforce, with engineering degrees being among the most common.

[16] Some contracts, such as the State of Tennessee RPA January 2002 Std 01252, specifically requires that the contractor consult NOAA data to determine anticipatable weather delays.

[17] ENSO also causes changes in U.S. temperatures, but this effect is generally weaker than the precipitation effect (Ropelewski and Halpert, 1987, Halpert and Ropelewski, 1992).

[18] For the latest seasonal forecasts from NOAA, extending out to 12.5 months, see here: https://www.cpc.ncep.noaa.gov/products/predictions/90day/

into the forecasts. But given the importance of ENSO to rainfall prediction in the U.S., ENSO variation likely plays an important role in guiding planning decisions by construction firms.

A strong El Niño event in 1982 and 1983 caused substantial rainfall across the U.S. and, over the next decade, led to increased public awareness of the link between ENSO and weather conditions.[19] The construction industry is well aware of the link between ENSO and rainfall. Articles in construction trade journals routinely report on the link between ENSO and U.S. rainfall, including emphasizing the need to prepare for changes in rainfall due to the climactic variation (Halsey, 2016). As Ropelewski and Halpert (1987) show and our results corroborate, the relationship between ENSO and rainfall is spatially heterogeneous, with some areas of the country experiencing heavier rainfall during ENSO events while other areas experience drier conditions. In our analysis, we will test whether ENSO-predicted rainfall affects employment, which implicitly assumes that the market is responding to the appropriate predictions for their area of the country. This assumption is plausible given that the spatial heterogeneity of ENSO effects has been known since at least the 1980s and the effects are consistent across broad areas of the country (the drier conditions are predominantly in the Northern Rockies and upper Midwest while wetter conditions are across the South and West Coast). In summary, then, the ENSO fluctuations that we use to generate variation in predictable rainfall are both the major driver of long-run rainfall forecasts *and* are a major focus of construction sector project managers.

3 Data

To estimate the effect of more or less forecastable rainfall on construction employment, we combine three primary data sources on employment, weather, and climate variability.

3.1 Construction employment data

We measure employment using the Quarterly Census of Employment and Wages (QCEW), which provides a high frequency snapshot of employment across U.S. counties based on state Unemployment Insurance records. Although we are primarily interested in firms' responses, we focus on aggregate data at the labor market level because existing firm-level datasets are not suitable for our purposes. Nearly all firm-level datasets are annual, while our approach requires high-frequency employment adjustments. Fortunately, the QCEW provides employment at the monthly frequency.

[19] See, for instance, the Washington Post's history of ENSO reporting by various news agencies (Williams, 2015).

While the Longitudinal Employer-Household Dynamics (LEHD) includes *quarterly* employment information (and would have other advantages), only since 2003 has it included all states. Prior to that, it includes only some states. This is a problem for us because part of our identifying variation comes from geographic variation in responsiveness to ENSO (thus, we need data from all states to provide enough cross-sectional variation) and part of our identifying variation comes from over-time variation in the ENSO index (thus, we need more over-time variation than the post-2003 period could provide). Figure A2 shows ENSO anomalies since 1990. Restricting to the post-2003 period would cost us the two highest ENSO spikes and the two lowest ENSO troughs.

3.2 Weather and climate data

The second main dataset we use contains rainfall and temperature measurements from the PRISM (Parameter-elevation Regressions on Independent Slopes) Climate Group (PRISM Climate Group, 2004). PRISM combines weather station data with elevation data to produce monthly, gridded measures of weather. The PRISM data provide more consistent geographic coverage than raw weather station data.

We aggregate the gridded measures to the CZ level by calculating population-weighted averages. The population weights come from the 2010 U.S. Census population grid available from the Center for International Earth Science Information Network (CIESIN, 2017). Figures showing the spatial variation in weather can be found in the appendix (Section A). The final weather dataset is a monthly panel from January 1990 to December 2016 of population-weighted average values for each CZ in the continental U.S. for total precipitation and average temperature.

Third, we use monthly data on ENSO from the NOAA as a source of long-range (monthly) predictability in rainfall. ENSO is commonly measured using sea surface temperature anomalies in an area of the equatorial Pacific Ocean known as the Niño 3.4 region that extends from 5°S to 5°N latitude and 170°W to 120°W longitude. Warm anomalies in this region are classified as El Niño events and cold anomalies are classified as La Niña events. We use the Niño 3.4 index as our measure of ENSO in the paper. The history of the Niño 3.4 index over our sample period is shown in Figure A2 (it is worth noting that ENSO is acyclical with respect to U.S. recessions).

As discussed in Section 2.2, ENSO is a crucial component of monthly or seasonal forecasts released by NOAA, ECMWF, and other forecasting groups. Technological advances concentrated during the 1980's led NOAA to begin releasing routine forecasts of monthly weather conditions starting in the middle of 1989 (Shrader, 2020). The timing of release of these forecasts and the growing public attention to ENSO-driven weather in the U.S. motivates our focus on the period after 1989.

3.3 Estimation sample and summary statistics

Combining all of the above datasets, we have an estimation sample consisting of monthly, CZ-level observations of employment in the construction industry, rainfall, temperature, and the Niño 3.4 index. The dataset runs from January 1990 through December 2016. After excluding CZs with suppressed construction employment, the final sample includes 633 out of the 722 CZs in the continental U.S.

Table 1: Summary Statistics

(a) Estimation Variables

Variable	Mean	Std. Dev.	Obs.
Construction employment	8604.4	22504.6	205,092
Monthly rain (mm)	78.4	61.9	205,092
Monthly avg. temperature (°C)	12.7	9.9	205,092
Niño 3.4 index (°C)	0.045	0.89	205,092

(b) Disclosed vs. Suppressed CZs

	Disclosed	Suppressed	Pct. disclosed
Number of commuting zones	633	90	88%
Total private employment (millions)	185.8	15.0	93%
Year 2000 Population (millions)	276.3	2.7	99%

Notes: The table shows summary statistics for the estimation sample (panel a) and information on the disclosed CZs that are included in the estimation sample versus the non-disclosed CZs that are excluded (panel b). The estimation sample consists of a balanced panel of 633 CZs observed for 324 months, resulting in 205,092 total observations.

Table 1 shows summary statistics for the main variables in our analysis. Employment is our primary outcome of interest. Rainfall, as forecasted by ENSO, is our primary right-hand side variable. Temperature is a control in the primary analysis. With 633 disclosed CZs observed monthly for 27 years, the final sample consists of 205,092 total observations.

Statistics on excluded CZs are also reported in panel (b) of the table. The first row shows that the CZs in our sample account for 93% of all reported private sector employment in the QCEW (which is subject to minimal suppression). The disclosed CZs account 99% of total population. These two figures show that the suppressed CZs are those that have minimal population and relatively small levels of employment. The final row shows that the disclosed sample is about 88% of all continental U.S. CZs. Figure A1 shows a map of the non-disclosed CZs. One can see that they are generally sparsely populated locations in the West.

4 Results

4.1 Predicting rainfall

Our core empirical specifications take the form of instrumental variables (IV) regressions, but the motivation for using IV is different than typical cases, and we use the terminology just to aid intuition for how the methodology works. The primary role of the first stage in each specification is to generate predictions of rainfall using variation in ENSO. Using an IV framework is beneficial because our estimates will correctly reflect inferential uncertainty from the generated regressors. The first stage for a given forecasting horizon ℓ is a regression of the form

$$
\begin{aligned}
\ln(Rain)_{c,t} =& \delta_t^1 + \rho_{c,m(t)}^1 + \gamma_c ENSO_{t-\ell} + \eta_c^1 ENSO_{t-\ell-6} \\
&+ \theta_{c,1}^1 \ln(Rain)_{c,t-1} + \theta_{c,2}^1 \ln(Rain)_{c,t-2} + \sum_{k=3}^{12} \pi_k^1 \ln(Rain)_{c,t-k} \\
&+ \sum_{k=1}^{12} \zeta_k^1 Temp_{c,t-k} + \nu_{c,t}
\end{aligned} \tag{1}
$$

where c indexes CZs and t indexes month. The index $m(t)$ is the month-of-year for month t.

We estimate one version of Equation (1) for each horizon $\ell \in \{1, \ldots, 6\}$. The regression tells us how fluctuations in ENSO at time $t - \ell$ map into time t rainfall in each CZ. We refer to ℓ as the forecasting horizon, and we vary the forecasting horizon to determine the employment effects of rainfall forecasts with longer and shorter anticipation horizons. The employment effects are discussed and reported in the next section.

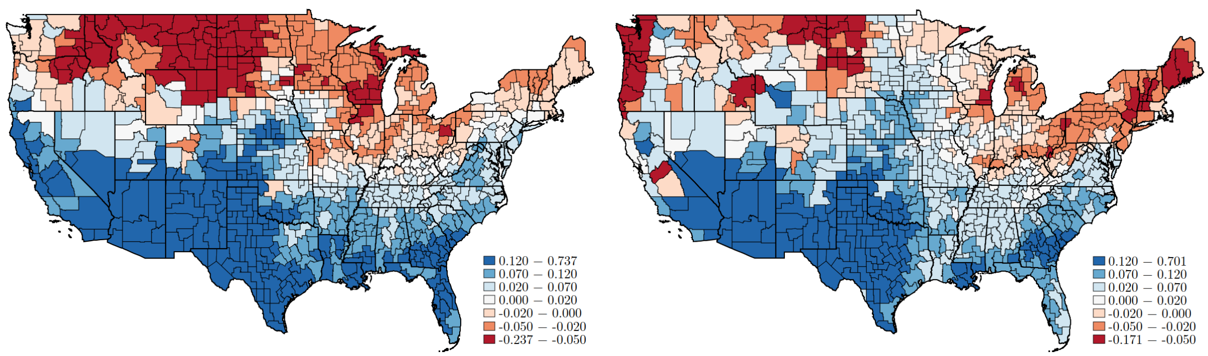
The key right-hand side variable is time $t - \ell$ ENSO interacted with CZ-specific coefficients. The coefficients capture regional variation in rainfall driven by ENSO. And these interaction terms are our excluded instruments in the second stage. Note that an additional, 6-month further lag of ENSO is also interacted with CZ-specific coefficients to account for serial correlation in ENSO. But this further lag is not excluded from the second stage, meaning that our first stage captures news about ENSO.

We identify the effect of ENSO on rainfall conditional on a number of controls. First, we include CZ by month-of-year fixed effects, $\rho_{c,m(t)}$, which subsume CZ fixed effects. These fixed effects condition out fixed features of the CZ as well as CZ-specific seasonal patterns that might otherwise lead to spurious relationships between rainfall and employment. We also include time fixed effects, which conditions out common time series patterns across the country. These fixed effects also condition out the time series pattern of ENSO, meaning that we are identified off of CZ-specific differences in the effect ENSO has on rainfall. The empirical specification can thus be viewed as a type of difference-in-differences estimator.

The first stage identifies locations where rainfall is affected by ENSO at different forecast horizons, ℓ. For a given horizon, the locations where ENSO has a strong effect will be the "treatment group" while locations where ENSO does not have a strong effect are the "control group."

Two of the further controls are of particular importance. CZ-specific coefficients on lags of rainfall isolate variation driven by ENSO from other types of regional weather fluctuations. One could use past realizations of rainfall to forecast future rainfall, but this strategy could be invalid if the past rain realizations themselves have persistent effects on productivity. We control for rainfall up until time t to prevent contamination of our results by persistent effects of rainfall that occurs prior to time t. We interact the first and second lag of rainfall with CZ fixed effects to ensure that we control for autocorrelation in rainfall at a level of granularity equal to our rainfall predictions.[20] Second, as discussed above, CZ-specific coefficients interacted with the $\ell + 6$ month lag of ENSO isolate news about ENSO that has arrived in the last 6 months. This gives us relatively precise information about the timing of the arrival of information. Knowing when information is arriving helps us characterize the dynamics of adjustment.

Figure 1: CZ-specific coefficients on ENSO



(a) $\ell = 1$ (b) $\ell = 6$

Figure displays CZ-specific coefficients from estimates of Equation (1). They show the response of log rain to a one standard deviation fluctuation in ENSO, depending on the time between the fluctuation and the rain (i.e., ℓ).

Figure 1 shows the CZ-specific effect of a one standard deviation increase in ENSO on log rainfall, conditional on all controls, as estimated by Equation (1). Panel (a) shows

[20]In practice, the employment effects we find are not highly sensitive to the inclusion or exclusion of the interaction between rain and CZ. If we simply include the lags of rainfall without any CZ interaction, the point estimate of the employment effect changes by 10% for the 1-month-ahead forecast and by 4% for the 6-month-ahead forecast, with precision improving in both cases. We maintain the interactions, however, based on our *a prior* preference for clearly isolating rainfall news in each CZ.

the coefficients for a short forecast horizon ($\ell = 1$), and panel (b) shows the coefficients for a long forecast horizon ($\ell = 6$). The overall pattern of results is consistent with the climatology literature on ENSO's teleconnection with rainfall in the U.S. (Ropelewski and Halpert, 1987). Like that previous literature, we find that ENSO tends to predict wetter conditions across the California coast, through the Southwest, and into the South. ENSO predicts drier conditions across the Norther Rockies, with some additional drying across the north of the country (Mason and Goddard, 2001). Appendix Figure A7 shows the empirical persistence of rainfall forecasted by the first stage. The figure shows that the forecasts predict higher rainfall over a period of 6 to 9 months, with the size of the rainfall shock falling monotonically over time. Persistence is similar across all forecast horizons we consider. The moderate empirical persistence of rainfall predicted by the forecast is helpful for identifying labor adjustment costs. If the rainfall shock was shorter-lived, then firms and workers would have less incentive to seek alternative work arraignments because the productivity costs of staying in construction would be lower.

The figure also highlights where our identifying variation comes from. As discussed above, we include time (year-month) fixed effects that perfectly absorb aggregate ENSO variation. Identifying variation comes from the different response of rainfall to ENSO at different horizons in different CZs. Focusing, for instance, on the Midwest in panel (a), we see that a one standard deviation increase in ENSO will raise rainfall in Western Iowa (along the Missouri River banks) by roughly 10%, while it will decrease rainfall in Eastern Iowa (along the Mississippi River banks) by a somewhat smaller amount.[21]

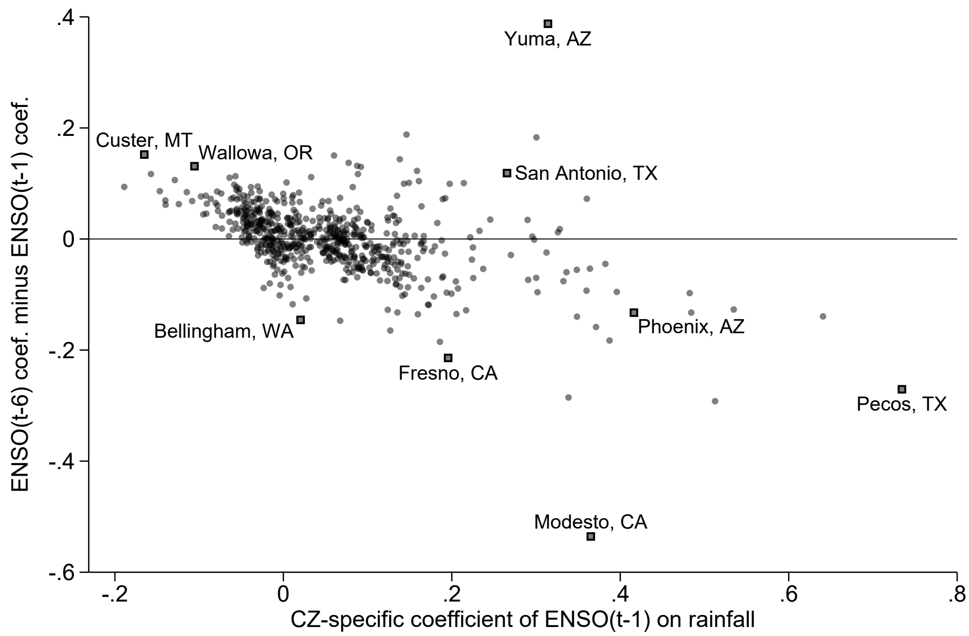
However, the variation we observe across locations is only part of what we use for identification. Again comparing panel (a) and panel (b), we also see that there is substantial variation in *when* ENSO predicts rainfall. In Western Virginia, for instance, ENSO increases rain the next month, but has little effect six months later. At the same time, in the neighboring CZs just north in Pennsylvania, ENSO has no effects initially but significantly reduces rainfall six months later. This type of idiosyncratic variation helps us separate responses depending on the timing of news arrival.

Figure 2 shows the differences in ENSO predictions at different forecast horizons to further clarify this second source of identifying variation. There is one point in the figure for each CZ in the sample. The points show the relationship between the CZ-specific ENSO coefficients from the version of Equation (1) estimated with the one-month lag of ENSO and the difference between the six-month lag coefficients and the one-month lag coefficients. In other words, the x-axis is the value of the γ_c coefficients from the $\ell = 1$ version of Equation (1). The y-axis is the difference between the $\ell = 6$ coefficients and the $\ell = 1$ coefficients.

[21]In Figure 1, CZs with a coefficient estimate greater than roughly 0.10 (in absolute value) are significant at the 5% level.

The main take-away from the figure is that there is appreciable variation in the relationship between ENSO and rainfall across time for the different CZs. We exploit these differences to identify the effect of different anticipation horizons.

Figure 2: Differences in First-stage Coefficients



Notes: The x-axis of the figure shows coefficient estimates from the 1-month ahead ($\ell = 1$) version of Equation (1). The y-axis is the difference between the 6-month ahead coefficients and the 1-month coefficients. There is one point for each CZ in our sample.

For example, focusing on rainfall responses at the 1-month horizon, there are hundreds of CZs where rainfall is close to non-responsive to ENSO (0 on the x-axis), and these are "control" CZ's. However, there are many more where ENSO increases rainfall, and even a handful where it *decreases* rainfall. At the extreme, in Pecos, TX, a one standard deviation increase in ENSO increases rainfall by 80 log points (120%).[22] This cross-sectional variation is one source of identification that we use.

We are also interested in how employment responses differ depending on the horizon of the forecast. This second source of identifying variation is shown by the y-axis. Consider, for example, Yuma, AZ, and Phoenix, AZ. These CZs are within the same state and are roughly equally responsive at the one-month horizon (.4, x-axis). But Yuma is twice as responsive at six months as it is at one month, while Phoenix is half as responsive. As a result of variation

[22]Figure A2 shows ENSO over time, measured in standard deviations. It is important to note that large and sudden shocks are not rare. For instance, in the late 1990's it rose by 2.5 standard deviations over less than a year, only to fall by 3.5 standard deviations a year later.

like this, two CZ's might experience the same short-run "ENSO treatment" but different long-run treatments, allowing us to separately identify responses to short-run and long-run forecasts.

The figure also gives an indication of the locations where rainfall tends to be more strongly associated with ENSO. Stronger ENSO predicts rainfall increases consistently across the South and Southwest of the U.S. from Texas to California, up the West Coast, and to a lesser extent in areas around Georgia down to Florida. Stronger ENSO predicts lower rainfall in the northern Rocky Mountains and upper Midwest.

Figure 2 shows the variation in forecast coefficients and gives a measure of magnitude.[23] One can get a further sense for the strength of the rainfall predictions of ENSO by examining the F-statistic for the instruments (ENSO interacted with CZ fixed effects) from the first stage regression. Because of the large number of variables we estimate (one for each CZ), we calculate a conservative, lower bound on the conventional F-statistic using a version of Equation (1) where we interact ENSO with a state fixed effect rather than a CZ fixed effect (holding everything else about the data and estimation fixed). This is a lower bound because it throws away all within-state variation from Figure 2. The resulting Montiel Olea and Pflueger (2013) effective F-statistic is 50.3 at a 1-month horizon and 40.0 at a 6-month horizon, compared to a critical value for worst case bias of 5% of 26.7 (see Table 2 for each horizon). At all forecast horizons, the ENSO-based predictions are strong and jointly significant.

The ENSO-driven forecasts substantially outperform simpler alternative forecasts. At a 1-month horizon, the correlation between realized rainfall and the ENSO-based forecast is 0.49 while the correlation with the one-month lag of rainfall is only 0.21. The quality of the ENSO forecast falls slightly at a 6-month horizon, with a correlation of 0.46, but again it outperforms the 6-month lag of rainfall, which has a correlation of only 0.07. The relatively small decline in quality is notable and comes from the fact that skill for the ENSO forecast derives, in part, from the timing of the relationship between ENSO and local rainfall. For example, in the CZ that contains Valley County, MT, the 1-month-ahead connection between ENSO and rainfall is strong (coefficient of -0.12) but the 6-month-ahead coefficient is 0.06. The probability that the ENSO-driven 1-month-ahead forecast correctly predicts above-average rainfall in the CZ is 0.62 while for the 6-month-ahead forecast it is 0.56, a difference of 6 percentage points. Dallas, TX exhibits the reverse pattern of ENSO-driven rainfall. There, the 6-month-ahead coefficient is a strong 0.36 while the 1-month-ahead coefficient is a relatively weaker 0.13 (although both coefficients indicate a robust connection between ENSO and rain). The 6-month-ahead ENSO forecast correctly predicts above-average rainfall 73% of the time—a value that increases by just 3 percentage points for the 1-month-ahead

[23]For the magnitude of the 6-month ahead forecast undifferenced, see Figure A4.

forecast. On average across all CZs, a 1% stronger connection to ENSO at a given horizon is associated with a 0.2% more accurate prediction of above-average rainfall.

4.2 Effect of predictable rainfall on employment

Our core interest is in employment adjustments in response to rainfall, depending on how far in advance that rainfall could be predicted. As discussed above, we rely on two sets of facts: first, that rainfall has important effects on construction sector productivity. Second, that ENSO fluctuations predict medium-term rainfall changes in the United States and that there is rich heterogeneity across place in how much and when these fluctuations translate into rainfall. This heterogeneity allows us to build an IV regression where we instrument for local rainfall using the CZ-specific ENSO response but are still able to control for CZ fixed effects (time-invariant geographic heterogeneity) and month fixed effects (arbitrary nationwide trends).

The second stage of the IV strategy is given by

$$\begin{aligned}\Delta_\ell \ln(Emp)_{c,t} =& \delta_t^2 + \rho_{c,m(t)}^2 + \beta_\ell \widehat{\ln(Rain)}_{c,t}^{\ell} + \eta_c^2 ENSO_{t-\ell-6} \\ &+ \theta_{c,1}^2 \ln(Rain)_{c,t-1} + \theta_{c,2}^2 \ln(Rain)_{c,t-2} + \sum_{k=3}^{12} \pi_k^2 \ln(Rain)_{c,t-k} \\ &+ \sum_{k=1}^{12} \zeta_k^2 Temp_{c,t-k} + \varepsilon_{c,t}\end{aligned} \tag{2}$$

where $\Delta_\ell \ln(Emp)_{c,t}$ is $\ln(Emp)_{c,t} - \ln(Emp)_{c,t-\ell-1}$. Estimating the effect on the change in employment reduces unit root concerns and helps eliminate confounding variables up to time $t-\ell-1$.[24] Estimating with lags of employment on the right-hand side yields similar estimates but requires the addition of employment lags in the first stage regression, so we prefer the specification here.

The primary right-hand side variable of interest is $\widehat{\ln(Rain)}_{c,t}^{\ell}$. The variable is generated by the first stage regression, Equation (1), and is the expected rainfall in CZ c at time t which could be forecast from information available ℓ months beforehand.[25]

The second stage includes every variable from the first stage except the excluded instruments: $ENSO_{t-\ell}$ interacted with CZ-specific indicators. In particular, it includes controls for lags of temperature (which improve precision), lags of realized rainfall, lags of ENSO in-

[24] Formal panel unit root tests using the Im et al. (2003) procedure reject the null that the series contains a unit root, but the high degree of autocorrelation in employment still leads us to prefer a specification in differences.

[25] The estimation is done using an IV strategy, so the hat on top of the rain variable is purely a notational reminder that the second stage regression involves unbiased rainfall *forecasts*.

teracted with CZ indicators, and fixed effects for the month and CZ by month-of-year. These controls remove confounding variation that is fixed within a location, that varies seasonally within a location, that varies over time nationwide (including the month-to-month variation in ENSO itself), and that might be caused by weather arriving before time t.

Table 2 displays estimated coefficients for the one through six-month ahead forecasts ($\ell \in \{1, ..., 6\}$) on employment at time t. There is a clear and monotonic pattern. Recall that rainfall substantially reduces construction productivity. Despite that, employment barely responds to rainfall increases that could only be predicted one month in advance. In contrast, employment is nearly five times as responsive to rainfall that could be predicted six months in advance, and the difference in response at the two different horizons is statistically significant at the 5% level.[26] The further ahead the increased rainfall could be predicted, the larger the employment response.

Table 2: Change in employment in response to predictable rainfall by length of forecast

DV: $\Delta_\ell \ln(Emp_t)$	(1)	(2)	(3)	(4)	(5)	(6)
Forecast length (ℓ):	1	2	3	4	5	6
$\widehat{\ln(Rain)}_t^{\ell}$	-.005*	-.010**	-.015**	-.017**	-.019**	-.026***
	(.003)	(.004)	(.006)	(.007)	(.008)	(.010)
First-stage Eff. F	50.3	46.5	45.3	42.7	42.0	40.0
R^2	.655	.707	.728	.730	.717	.689
N	194,947	194,947	194,947	194,947	194,947	194,947

* $p < .10$, ** $p < .05$, *** $p < .01$. Table displays estimated elasticities of the response of employment at time t to rainfall estimated at time $t-\ell$ to occur at time t. Standard errors clustered at the CZ level are in parentheses. All estimates come from IV regressions that include time fixed effects, CZ fixed effects, and CZ-by-month-of-year fixed effects, as well as lagged rainfall, employment, and temperature controls shown in the estimating equations (1) (first stage) and (2) (second stage). Rainfall predictions are the primary explanatory variable and are based on CZ-specific responses to changes in ENSO. The strength of the first-stage instruments (CZ-specific ENSO effects) is indicated by the Montiel Olea and Pflueger (2013) effective F-statistics in the third-from-last row.

Why might employment respond more to forecasts available further in advance? One explanation is that labor market frictions and adjustment costs make instantaneous responses costly.[27] Above, we discussed several of these costs, such as implicit layoff taxes generated

[26] While few of the other coefficients are statistically significantly different from one another, the monotonic pattern and difference in magnitudes is clear. The calibration described in Section 5 reflects the uncertainty in these parameter estimates.

[27] If people respond differently to relatively accurate forecasts (due to risk aversion, for instance), then

by the financing rules of the unemployment insurance system.[28] We also discussed a series of costs in terms of recruiting, screening, and hiring. It is important to keep in mind that these hiring costs are relevant for firms even if our empirical results reflect employment *decreases* in response to increased rain. This is because rainfall is only a temporary productivity shock. Firms will soon need to re-staff after excess rain subsides, and hiring new workers will require paying those costs.

Recognizing this, a firm which suddenly discovers that it will face a negative productivity shock during the next month (estimates for $\ell = 1$) might simply prefer to continue to employ less productive workers for a short time rather than laying them off and having to replace them through a costly screening process soon after. After all, the costs of replacing a worker are roughly equal to one month salary (Dube et al., 2010), and it is unlikely that workers' productivity falls all the way to zero during the period of excess rain. A firm which discovers that it has six months until that productivity decline, on the other hand, can take advantage of the regular turnover process and simply delay hiring replacements for those who leave.[29]

Whether or not this is realistic depends on the rate of natural turnover in construction, as well as the magnitude of the rain-induced employment responses that we document. The turnover rate can be measured using linked Current Population Survey (CPS) data, which shows that in a given month, 2% of construction workers leave their current employer for another. To understand the magnitudes of the responses that we identify, consider a very ENSO-responsive CZ that sees rainfall rise by 40 log points in response to a one standard deviation ENSO shock (the heterogeneity in ENSO-responsiveness is given in Figure 2). At the 6-month horizon, when employment shows the greatest responses, the second stage estimates in Table 2 suggest that this translates into a roughly 1% decline in employment.[30] It is not difficult to imagine a firm with one-month departure rates of 2% managing a 6-month decline of 1% exclusively using hiring delays. At the same time, this effect size shows that employment responses to anticipatable rainfall are non-trivial. The size of the effect we find in comparison to month-to-month turnover suggests that the estimates are plausible and reinforce the industry journals cited in Section 2 discussing the important, negative effects of rainfall on productivity.

One way to empirically assess the productivity effects associated with ENSO-driven rain

one could also find differences in response. But as we note in the previous section, the forecast quality is roughly similar across the horizons we consider. And if people respond *more* to more accurate forecasts, then it would lead to the reverse of the pattern we find.

[28] Again, even in the absence of rules like these, if sudden firing raises workers' perceptions of the riskiness of the job, then it can still be costly to firms who have to renegotiate higher wages to compensate workers for risk (as argued by Smith (1776)).

[29] Similarly, one can consider firms to be paying to retain less productive workers during a brief, negative shock rather than bear the costs of hiring new workers after the shock is over. We emphasize hiring as a prelude to our model setup below.

[30] $\exp\{.4 \times -.026\} = .9896$

is to regress construction-sector wages on surprise rainfall, with the logic being that there cannot be any *ex ante* adjustment of employment to surprise rainfall. The QCEW only reports data on the wage bill on a quarterly basis, so we cannot perfectly replicate our baseline employment analysis, but Table A1 reports estimates of the quarterly analogue of Equation (2) where the dependent variable is log wage bill and the main independent variable is the portion of realized rain that is associated contemporaneously with ENSO.[31] The regression shows that a 1% increase in surprise rainfall decreases earnings by 0.038%. Given that the results are based on the wage bill and that we find little to no employment response to more surprising rainfall, the effect could come through changes in the wage or hours worked.

These reduced form estimates and back-of-the-envelope calculations are useful for empirically identifying market responses. By themselves, however, they do not allow us to understand the implications of rainfall shocks for worker and firm outcomes (aside from employment changes), and they do not allow us to derive quantitative implications of rising rainfall volatility driven by climate change. In the next section, we develop a model of employment dynamics that links them to adjustment costs for workers and firms. We use our reduced form estimates of the employment responses to calibrate the adjustment costs that firms face, and use this to quantify the consequences of rising rainfall volatility and the value of improving the quality of forecasts.

5 Model and counterfactuals

5.1 Model of labor market with adjustment costs

The elasticity estimates in Table 2 capture the response of the construction sector within a local labor market to news about rain. These responses reflect both the adjustment of the supply of labor in the construction industry as well as demand for labor by construction firms. In turn, adjustments on both sides of the market reflect conditions in other sectors of the economy. For example, construction services are intensively used for investment, so demand for construction services reflects investment decisions throughout the local labor market. To account for these cross-sector linkages, we model the entire local labor market's response to rain, incorporating spillover effects through the input-output structure of the economy.

We model the local labor market as a small, open, multi-sector economy, populated by firms in each sector and a representative household. This model features a number

[31] As in the employment regressions, we control for previous news about ENSO as well as previous meteorological conditions. In other words, we regress quarterly, CZ-level construction-sector wage bill on $\ln\widehat{(Rain)}_t^0$ as generated by a quarterly version of Equation (1), plus quarterly versions of the baseline control variables.

of elements common to standard multi-sector models in the spatial economics literature (Redding and Rossi-Hansberg, 2017). For example, to capture cross-sector spillover effects, we incorporate intermediate inputs and calibrate to match the input-output structure of the economy, and to model frictions to labor adjustment on the supply side of the market, we incorporate heterogeneous Gumbel preferences of households across sectors and time (Caliendo and Parro, 2015, Caliendo et al., 2018, 2019). To model frictions on the demand side, we incorporate convex adjustment costs to hiring by firms (Muehlemann and Pfeifer, 2016). In our counterfactuals, we focus on the importance of different levels of adjustment costs for firms. We introduce these costs as employees diverted from production when a firm changes their hiring rate over time.

We begin by describing the input-output structure of the economy. In order to calibrate the model directly to make and use input-output tables from the Bureau of Economic Analysis (BEA), we model each sector's output as a local good that is non-traded, and model the commodities used by households, firms, and the government for consumption, intermediate inputs, real estate investment, and capital formation as (potentially) traded goods. There are N sectors, which we index with i, and J commodities, indexed by j. Local sector output, denoted by Y_{it}, gets combined together into commodities according to a Cobb-Douglas technology:

$$X_{jt}^{S} = \prod_{i=1}^{M} \left(\frac{Y_{it}}{\Phi_{ij}} \right)^{\Phi_{ij}}. \tag{3}$$

Here, X_{jt}^{S} is the quantity of commodity j supplied by the local economy and $\Phi_{ij} \geq 0$ is a Cobb-Douglas weight with $\sum_{i=1}^{N} \Phi_{ij} = 1$. We assume that this local supply of commodities gets produced under perfect competition, which links the price of commodities, P_{jt}, to the price of sectoral output, P_{it}^{Y} as

$$P_{jt} = \prod_{i=1}^{M} (P_{it}^{Y})^{\Phi_{ij}} \tag{4}$$

and implies that Φ_{ij} is the share of local commodity revenue paid to each sector, so that total revenue of i is $P_{it}^{Y} Y_{it} = \sum_{k=1}^{J} \Phi_{ij} P_{jt} X_{jt}^{S}$. We calibrate these shares to match the corresponding revenue shares in the make tables from the BEA. Note that for non-traded commodities, this local supply of commodities will need to equal local demand for commodities in equilibrium. We discuss the market clearing conditions when we turn to defining equilibrium below.

Next, we turn to the production of Y_{it} by local firms under perfect competition. The output of each firm in sector i at time t is Cobb-Douglas in capital, K_{it}; labor used in production, L_{it}; and an index for commodities used as materials, M_{it}.

$$Y_{it} = A_{it} \left(K_{it}^{\alpha_i} L_{it}^{1-\alpha_i} \right)^{1-\gamma_i} M_{it}^{\gamma_i} \quad \text{where} \quad M_{it} = \prod_{j=1}^{J} \left(\frac{M_{ijt}}{\Gamma_{ij}} \right)^{\Gamma_{ij}/\gamma_i} \tag{5}$$

with $\gamma_i \equiv \sum_{j=1}^{J} \Gamma_{ij} < 1$, and $\Gamma_{ij} \geq 0$. The variable M_{ijt} denotes sector i's demand for commodity j, and the variable A_{it} denotes total factor productivity. We assume that realized rainfall impacts construction sector productivity, but does not impact other sectors:

$$\ln A_{it} = \ln \bar{A}_i - \mathbf{1}\{i = \text{Construction}\}\epsilon \ln \text{Rain}_t. \tag{6}$$

Here, $\bar{A}_i$ is a sector-specific constant, while ϵ is the elasticity of construction sector productivity to realized rain.[32]

Due to perfect competition, γ_i is the share of firm revenue spent on materials,

$$P_{it}^{M} M_{it} = \gamma_i P_{it}^{Y} Y_{it} \quad \text{where} \quad P_{it}^{M} = \prod_{j=1}^{J} P_{jt}^{\Gamma_{ij}/\gamma_i}. \tag{7}$$

Here, P_{it}^{M} is an index of materials costs for the sector given commodity prices. The purchases of commodity j are

$$P_{jt} M_{ijt} = \Gamma_{ij} P_{it}^{Y} Y_{it}. \tag{8}$$

Additionally, α_i is the share of revenue net of material costs (value-added) paid to capital,

$$R_t K_{it} = \alpha_i (P_{it}^{Y} Y_{it} - P_{it}^{M} M_{it}) = \alpha_i (1 - \gamma_i) P_{it}^{Y} Y_{it}, \tag{9}$$

where R_t is the capital rental rate, which, for simplicity, we assume is common across sectors due to mobile capital.

In the absence of frictions to hiring labor, the firm would pay a fraction $1 - \alpha_i$ of value-added to labor. However, we assume that hiring is costly for the firm because it requires the use of employees devoted to the task. The productive labor input of the firm consists of those employees which it does not need to devote to hiring new workers. Given its current number of workers, N_{it}, the fraction of its labor force that must be devoted to hiring is

$$1 - \frac{L_{it}}{N_{it}} = \frac{\kappa}{2} \left(\frac{H_{it} - H_{i,t-1}}{H_{i,t-1}} \right)^2 \tag{10}$$

If a firm in steady state ($H_{it} = H_{i,t-1}$) wants to increase or decrease its hiring rate, then it must divert some of its workforce away from production. These costs are convex so that larger deviations of H_{it} from $H_{i,t-1}$ incur greater costs, and κ is the key parameter that pins down the magnitude of these hiring costs. To allow for non-zero adjustment costs in all sectors while keeping a parsimonious specification, we make the simplifying assumption that

[32] In Appendix Table A7, we show that allowing rain to also impact productivity in the agriculture industry (either positively or negatively) does not significantly change our model's predictions for the elasticity of construction employment to anticipated rain.

this parameter is common across sectors.[33]

The importance of hiring adjustment costs can be seen through the first order condition for new hires, which states that the marginal benefit of a new worker must equal the marginal cost of a new hire. The marginal benefit is forward looking because workers may stay with the firm for many periods. In particular, the firm's employment evolves as

$$N_{it} = (1-s)\Pi^{\text{Stay}}_{i,t} N_{i,t-1} + H_{it} \tag{11}$$

where $\Pi^{\text{Stay}}_{i,t}$ is the fraction of the firm's past employees who stay in the sector, and s is the fraction of these workers who separate from the firm and must find a new job in the sector. The first term captures the total number of workers who stay with the firm over time.

Given the law of motion in (11), the shadow value of another worker to the firm, V_{it}, satisfies the following forward looking condition.

$$V_{it} = P^Y_{it} MPL_{it} \frac{L_{it}}{N_{it}} - W_{it} + \frac{1-s}{1+r} \mathbb{E}_t \Pi^{\text{Stay}}_{i,t+1} V_{i,t+1} \tag{12}$$

where P^Y_{it} denotes the competitive price of sector i output, $MPL_{it} \equiv (1-\alpha_i)(1-\gamma_i)\frac{Y_{it}}{L_{it}}$ is the marginal product of labor, W_{it} denotes the competitive wage in sector i, and r denotes the interest rate at which the firm is externally financed. The firm values a worker based on the expected discounted value of the gap between the marginal revenue product of labor and the wage, accounting for the chance that the worker stays with the firm over time. When the firm anticipates that future marginal revenue products will be high relative to wages, it will value building up its current labor force.

It will do so trading off these benefits against current hiring costs. That is, the value of an additional worker must equal the marginal cost of hiring an additional worker.

$$V_{it} = P^Y_{it} MPL_{it} \kappa \left(\frac{H_{it} - H_{i,t-1}}{H_{i,t-1}} \right) \frac{N_{it}}{H_{i,t-1}} - \mathbb{E}_t \frac{P^Y_{i,t+1} MPL_{i,t+1}}{1+r} \kappa \left(\frac{H_{i,t+1} - H_{it}}{H_{it}} \right) \frac{H_{i,t+1}}{H_{it}} \frac{N_{i,t+1}}{H_{it}} \tag{13}$$

The expression for the marginal cost has two terms. The first represents the cost to the firm from reduced output in the present due to diverting labor toward hiring, while the second represents the gain to the firm from avoiding future lost output. When the value of additional workers is high in the present, the firm will be more willing to forego present output to build up its labor force through hiring.

[33] Although this assumption is inconsistent with evidence that adjustment costs are higher in high wage industries (Muehlemann and Pfeifer, 2016), our results are robust to including heterogeneity in κ. In Appendix Table A8, we show that the heterogeneity estimated in Muehlemann and Pfeifer (2016) as well as extreme forms of heterogeneity do not appreciably change our model's predictions for the elasticity of construction employment to anticipated rain.

Notice that in the absence of hiring costs (when $\kappa = 0$), the firm will hire additional workers until the marginal benefit of hiring is zero. In this case, because $V_{it} = 0$, the valuation condition in (12) reduces to stating that the wage must equal the marginal revenue product of labor. In this special case, $1 - \alpha_i$ is the faction of value added paid to labor. When $\kappa > 0$, hiring adjustment costs lead to departures from the equalization of wages to the marginal revenue product of labor, and link hiring decisions to the anticipated future gaps between the marginal revenue product and wages. When the present value of these gaps is positive, the firm will tend to increase its hiring. News of reduced future productivity in the construction sector—such as increases in forecasts of rain—will reduce the value of hiring workers today, leading to current reductions in employment.

Of course, the total impact of reductions in future productivity depend also on the response of labor supply. Workers will also anticipate that they will face low future wages, and, if they also face adjustment costs, they will want to exit the sector preemptively to avoid being stuck with low income in the future.

To capture this possibility and maintain tractability, we assume that workers are members of a representative household that provides perfect consumption and housing insurance, and that allocates individuals to work across sectors. In addition to working in a sector, each individual can also be non-employed. Let $i = 0$ index this non-employment state, and denote individual n's employment status at time t as $i_t(n) \in \{0, 1, \dots, N\}$. Given discount factor $\beta \in [0, 1)$, average expected discounted utility of household members is

$$\mathcal{U}_t = \sum_{h=0}^{\infty} \beta^h \left[\ln C_{t+h} + \mu^S \ln S_{t+h} + \int_0^1 \nu_{i_{t+h-1}(n), i_{t+h}(n), t+h}(n) \mathrm{d}n \right] \text{ where } C_t = \prod_{j=1}^{J} (C_{jt}/\mu_j^C)^{\mu_j^C} \tag{14}$$

where μ_j^C is the share of consumption expenditure on commodity j, S_t denotes housing services (equal to the stock of housing), μ^S captures the importance of housing services, and $\nu_{i,i',t}(n)$ is an individual preference shock for transitioning from i at $t-1$ to i' at time t. These preference shocks generate heterogeneity in how workers decide to switch sectors throughout their career. Changes in relative wages across sectors (driven by productivity shocks to the construction sector, for example) can drive these decisions, but these preference shocks allow workers to have disutility from leaving their job, or from switching sectors even in the absence of pecuniary benefits to doing so.

We assume that these preference shocks are Gumbel distributed independently across i' with shape $1/\theta$ and independently and identically distributed over time and individuals. The parameter θ captures heterogeneity across workers in their preferences to switch sectors. When θ is low, there is low dispersion across individuals so individuals are more willing to shift across sectors as the value of employment in each sector changes. In other words, when other factors like family needs, geographic mobility, injury, or aging or educational attainment (all of which we model in a reduced form way as a preference shock) are unimportant, then θ will be low implying little dispersion in preferences, and workers will be very responsive to changes in relative pay across sectors. We interpret this as suggesting very low adjustment costs (on the household side), because workers are very willing to respond to monetary incentives. If, on the other hand, θ is high, then dispersion in non-monetary preferences is large, and mobility responses to shocks to the relative wage will be muted.

For each moment in time, the representative household chooses consumption, housing investment, and an allocation of individuals across industries to maximize the expected discounted average utility of its members subject to its budget constraint and a housing law of motion. Its budget constraint is

$$\sum_{j=1}^{J} P_{jt}(C_{jt} + I_{jt}^S) \leq \sum_{i=0}^{M} W_{it} N_{it} + T_t \tag{15}$$

where I_{jt}^S denotes purchases of commodity j for investment in housing, W_{it} denotes income from employment status of i at time t—either the wage in a sector or income when non-employed—and T_t denotes net taxes and transfers from the government. The household's housing investment technology is

$$S_t = (1 - \delta^S) S_{t-1} + I_t^S \quad \text{where} \quad I_t^S \equiv \prod_{j=1}^{J} \left(\frac{I_{jt}^S}{\mu_j^S} \right)^{\mu_j^S}. \tag{16}$$

The parameter δ^S is the housing depreciation rate, and μ_j^S is the share of housing investment expenditure on commodity j.

The solution to the consumption and investment portion of the representative household's problem can be characterized as follows. The costs to the household of consumption and new housing at time t are, respectively,

$$P_t^C = \prod_{j=1}^{J} P_{jt}^{\mu_j^C} \quad \text{and} \quad P_t^S = \prod_{j=1}^{J} P_{jt}^{\mu_j^S} \tag{17}$$

and consumption and real estate investment expenditure on commodities satisfy, respectively,

$$P_{jt} C_{jt} = \mu_j^C P_t^C C_t \quad \text{and} \quad P_{jt} I_{jt}^S = \mu_j^S P_t^H I_t^S. \tag{18}$$

This result allows us to calibrate household consumption preferences and the housing investment technology using data on each commodity's share of total consumption and residential investment expenditure.

Investment in housing is characterized in terms of these price indices by

$$\mu^S \frac{C_t}{S_t} = \frac{P_t^S}{P_t^C} - \beta(1-\delta^S)\mathbb{E}_t \frac{C_t}{C_{t+1}} \frac{P_{t+1}^S}{P_{t+1}^C}. \tag{19}$$

This condition states that the marginal rate of substitution between consumption and housing services has to equal the user cost of an additional unit of housing in units of consumption. The later can be interpreted as the implicit rental price of the housing stock in units of consumption. As a consequence, we can calibrate μ^S to the ratio of implicit rent on housing services to total consumption expenditure.

Finally, we focus on the allocation of workers across industries. Under our Gumbel assumption on idiosyncratic preference shocks, the utility value of allocating another worker to employment status i during period t is

$$U_{it} = \frac{W_{it}/P_t^C}{C_t} + \beta\mathbb{E}_t \left[\theta \ln \sum_{i'=0}^{M} \omega_{i,i'} e^{U_{i',t+1}/\theta} \right] \tag{20}$$

where $\omega_{i,i'} \geq 0$ with $\sum_{i'=0}^{M} \omega_{i,i'} = 1$ captures average preferences for transitioning from i to i'. The value of an additional worker in sector i depends on the marginal utility value of the real wage in that sector as well as anticipated future real wages across all industries, accounting for the chance of reallocating the worker in the future. In this way, labor supply is forward looking, with future wages impacting the current allocation of workers across industries.

Specifically, the share of workers shifting from i at time $t-1$ to i' at time t is

$$\Pi_{i,i',t} = \frac{\omega_{i,i'} \exp(U_{i',t}/\theta)}{\sum_{\tilde{i}=0}^{M} \omega_{i,\tilde{i}} \exp(U_{\tilde{i},t}/\theta)} \tag{21}$$

leading to the following employment law of motion

$$N_{i't} = \sum_{i=0}^{M} \Pi_{i,i',t} N_{i,t-1}. \tag{22}$$

This result provides an interpretation for $\omega_{i,i'}$ as the share of workers transitioning when all employment statuses have equal value (when $U_{i't} = U_{it}$ for all i', i). It also shows that $1/\theta$ is the semi-elasticity of employment flows to changes in the value of employment. When labor supply adjustment costs are high, it takes a larger change in the value of employment to generate a shift of workers across sectors.

To close the model, we assume that absentee investors own the local capital stock and are financed at the same interest rate as firms, r. They accumulate capital through an investment technology that is Cobb-Douglas in commodities

$$K_{t+1} = (1-\delta^K)K_t + I_t^K, \quad \text{and} \quad I_t^K \equiv \prod_{j=1}^{J} (I_{jt}^K)^{\mu_j^K}. \tag{23}$$

where I_{jt}^K denotes purchases of commodity j for capital investment. Under this assumption, the cost of a new unit of capital, and capital investment expenditure are, respectively,

$$P_t^K = \prod_{j=1}^{J} P_{jt}^{\mu_j^K} \quad \text{and} \quad P_{jt} I_{jt}^K = \mu_j^M P_t^K I_t^K. \tag{24}$$

The capital investor's no-arbitrage condition is

$$\frac{1}{1+r}\mathbb{E}_t R_{t+1} = P_t^K - \frac{1-\delta^K}{1+r}\mathbb{E}_t P_{t+1}^K$$

The expected discounted capital rental rate must equal the user cost of capital.

With this final assumption, we can now define equilibrium. Given an exogenous process for rain in the local economy, $\{\text{Rain}_t\}_{t=1}^{\infty}$, a set of traded commodities, $\mathcal{J}$, with exogenous prices $\{Z_{jt}\}_{j\in\mathcal{J}}$, an initial condition for capital of K_1, initial conditions for labor $\{N_{i0}\}_{i=0}^{N}$, an initial condition for hiring, $\{H_{i0}\}_{i=1}^{N}$, exogenous government expenditure on commodities of $\{G_j\}_{j=1}^{J}$, exogenous transfers of $\{T_t\}_{t=1}^{\infty}$, exogenous non-employment compensation of $\{W_{0t}\}_{t=1}^{\infty}$, and an external interest rate of r, a rational expectations equilibrium is a stochastic process for prices/valuations

$$\{\{P_{jt}\}_{j=1}^{J}, \{P_{it}^Y\}_{i=1}^{N}, \{P_{it}^M\}_{i=1}^{N}, P_t^C, P_t^S, P_t^K, R_t, \{V_{it}, W_{it}\}_{i=1}^{N}, \{U_{it}\}_{i=0}^{N}\}_{t=1}^{\infty}$$

and quantities

$$\{\{X_{jt}^S\}_{j=1}^{J}, \{Y_{it}\}_{i=1}^{N}, \{M_{it}\}_{i=1}^{N}, \{H_{it}\}_{i=1}^{N}, C_t, \{C_{jt}\}_{j=1}^{J}, S_t, \{I_{jt}^S\}_{j=1}^{J}, K_{t+1}, \{I_{jt}^K\}_{j=1}^{J}, \{N_{it}\}_{i=0}^{N}\}_{t=1}^{\infty}$$

such that

1. **(Local Commodity Supply)** Local production of commodities satisfies (3), expenditure on sector i output is $P_{it}^Y Y_{it} = \sum_{j=1}^{J} \Phi_{ij} P_{jt} X_{jt}^S$, and commodity and sectoral output prices satisfy (4).

2. **(Firms)** Local sectoral output is given by (5) for productivity given rain satisfying (6), total materials satisfying (7), commodity-level materials satisfying (8), capital demand satisfying (9), labor in production satisfying (10), labor demand satisfying (11), the value of an additional worker satisfying (12), and hiring satisfying (13).

3. **(Households)** The household stock of housing evolves as (16), the prices of consumption and new housing are (17), commodity level consumption and expenditure satisfy (18), housing demand satisfies (19), the value of allocating a household member to i is (20), and the flow of household members from i to i' is (21) so that the allocation of workers satisfies (22).

4. **(Capital Supply)** The supply of capital evolves as (23) with the price of investment and investment demand satisfying (24).

5. **(Factor Market Clearing)** The supply of capital equals total demand across sectors, $K_t = \sum_{i=1}^{N} K_{it}$, firm level labor demand in (11) corresponds to the supply of workers provided by households in (22).

6. **(Traded Commodity Prices)** For each traded commodity $j \in \mathcal{J}$, the local price of commodity output equals the external price: $P_{jt} = Z_{jt}$.

7. **(Non-Traded Commodity Local Market Clearing)** For each non-traded commodity $j \notin \mathcal{J}$, total local supply of the commodity equals total local demand:

$$X_{jt}^S = \sum_{i=1}^{N} M_{ijt} + C_{jt} + I_{jt}^S + I_{jt}^K + G_j.$$

5.2 Calibration

We calibrate the model to match input-output tables from BEA, monthly employment transition rates across sectors from the Current Population Survey, and a 2% annual percentage rate for household discounting and the firm's interest rate. See Appendix B.1 for summary statistics of the calibration. This pins down all parameters except those controlling adjustment costs, the effect of rainfall on construction productivity, and the impulse response of rainfall to news about rain.

To model the arrival of news about future rain, we specify the following stochastic process for rain.

$$\ln \text{Rain}_t = \sum_{k=1}^{5} \rho_k \ln \text{Rain}_{t-k} + \upsilon_t \quad \text{with} \quad \upsilon_t = \sum_{\ell=0}^{L} n_{t,t-\ell} \tag{25}$$

Here, υ_t is the realized shock to rain at time t, while $n_{t,t-\ell}$ denotes the component of this realized rain shock that is known at time $t-\ell$. The key assumption in this equation is that news shocks of the same size but at different horizons generate the same change in shocks to realized rain. The parameters $(\rho_1, \ldots, \rho_5)$, allow us to capture persistence to changes in rainfall after a shock to rain. Since firms and workers anticipate future rain in making their decisions within the model, they may respond differently to the shock depending on its persistence.

Accordingly, we discipline these persistence parameters using a two step procedure. First, we estimate the empirical impulse response of rainfall after time t to our forecasts of rainfall at time $t-\ell$ for $\ell = 1, \ldots, 6$ by running (2) where the dependent variable is log realized rain. Note that this specification includes controls for realized rain on the right hand side up until time t, so the coefficient estimates are mechanically zero for $h < 0$. The empirical magnitude of the impact of news by horizon is similar across ℓ, consistent with our assumption that news shocks have the same impact on rain shocks. In the second step, we match these estimates by pooling across ℓ and choose the persistence parameters ρ_1 to ρ_5 to minimize the sum of the squared difference between the first step estimates and the autoregressive model after scaling by the first step standard errors. See Figure A7 in the appendix for the fitted response.

The elasticity of construction productivity to rain, ϵ, controls the overall magnitude of responses of the economy to rain shocks. Intuitively, changes in productivity get passed through into wages, so we choose this parameter such that the model generates quarterly average impacts of contemporaneous rain on the wage bill that match our empirical estimate reported in A1.

To estimate the labor supply and demand adjustment cost parameters, θ and κ, we minimize the distance between the model's normalized prediction for adjustment of construction employment to news about rain and our estimates in Table 2. This provides six target moments for the two labor adjustment cost parameters.

Recall that θ measures the degree of heterogeneity in worker preferences for moving across sectors. A low value of θ would mean that workers are relatively homogeneous, so for a given change in the value of being in a sector, a large fraction of the workers would want to change their sector. High values imply that it would take a large shift in value to induce substantial movement of workers across sectors. Thus, we view θ as capturing labor supply adjustment costs.

The κ parameter measures demand side adjustment costs. It is the cost to the firm of adjusting its hiring rate, as shown in Equation (10). For a higher value of κ, firms must devote more of their production toward hiring efforts (for instance by using more time for interviews, advertising positions, reviewing applications, or training).

The values for θ and κ that best fit the set of empirical rainfall forecast and employment elasticities are shown in Table 3. We can interpret the estimate of θ using Equations (20) and (21). The inverse of θ is the semi-elasticity of employment flows to the value of employment. An increase in the real wage difference between two sectors in a single month by 100% of steady state consumption (holding fixed expectations of the future value of both sectors)

Table 3: Inferred Parameters and Model Fit

Estimates		Fit By Horizon							
	Value	h	0	-1	-2	-3	-4	-5	-6
θ	32.7	Uncentered R^2	99.6%	98.2%	98.1%	96.4%	94.4%	94.5%	95.9%
κ	65.5	Centered R^2	97.3%	93.9%	93.6%	89.3%	85.2%	83.8%	-
ϵ	0.17	ℓ	1 to 6	1 to 6	2 to 6	3 to 6	4 to 6	5 and 6	6
		Target Moments	✓						

Notes: Parameter values minimize the mean squared error in the target moments between the estimates and the model with ϵ chosen to scale the average of model predictions to match the average of estimates across ℓ. We omit the centered R^2 at horizon 6 because there is only one comparison value so it is mechanically 100%.

will increase the odds that a worker changes sectors by 3% during that month.[34]

Using Equation (10), the estimate of κ implies that devoting 1% of a firm's labor force to hiring rather than production during a month will generate a 1.7% increase in the firm's hiring rate, while devoting 10% of the labor force generates a 5.5% increase in the hiring rate during that month. Previous work also finds convexity in hiring costs using firm-level data (Muehlemann and Pfeifer, 2016). The value we find is larger than those previous estimates, although caution must be taken with direct comparison because the model calibration provides estimates of marginal hiring costs while the prior empirical work estimates average costs.[35]

Intuition on how the model determines the appropriate level of κ can be gained from the visualization in Figure 3. When κ is low (adjustment is less costly), employment responds strongly to news about rain at all horizons. When κ is high all employment responses are low. The scale of response is not the only difference. In both cases, differences across forecast horizon are small relative to differences across horizon when κ is at our baseline estimate. In that case, the responses are spread out across news horizon. This spreading captures the importance to the firm of smoothing out hiring over time in the presence of convex hiring costs. Intuitively, if adjustment costs are prohibitive, no adjustment occurs, while when adjustment costs are low, adjustment happens easily and there is little need to smooth over time. When adjustment costs are moderate, the employment responses get spread out.

Table 3 also shows measures of model fit, both for the target moments—the elasticities of employment with respect to rainfall forecasts at the time when rainfall arrives—and for

[34] That is, $\ln \frac{\Pi_{i,i',t}}{\Pi_{i,i,t}}$ changes by .03 $(1/\theta)$ when $(W_{it} - W_{i't})/P_t^C$ increases by 100% of steady state consumption.

[35] In sensitivity analysis reported in Table A8, we show that allowing heterogeneity in κ across sectors does not appreciably change the results we report for the construction industry.

non-target moments of that same elasticity for months after news has arrived but before the rainfall shock has occurred. The empirical estimates for these moments can be found in Figure A6. The table reports R^2 values that are the amount of variation in the empirical point estimates that is explained by the model-derived employment elasticities. One can see that even for these non-targeted moments, the model fits well, with a minimum R^2 of 84%.

5.3 Counterfactuals

One advantage of our model is that it allows us to interpret the rainfall shocks that we observe in more meaningful units. Using our benchmark calibration, we find that a one standard deviation above-mean rainfall shock is equivalent to an 17% loss of productivity. A 17% productivity decline is clearly meaningful, and in this section, we focus on how firms respond, how the costs of this shock are shared between workers and firms, and how the size of adjustment costs determines these responses.

Because our primary interest is in how firms might improve their ability to adapt (e.g., by negotiating more flexible labor contracts with workers or by diversifying their mix of projects to allow project-specific labor levels to be more responsive), we keep worker-side adjustment costs (θ) constant at the level of our baseline calibration. Instead, our counterfactuals focus on how changes in *firms'* ability to respond to shocks (κ) affects their employment dynamics and profits, as well as how this interacts with the quality of weather forecasts.

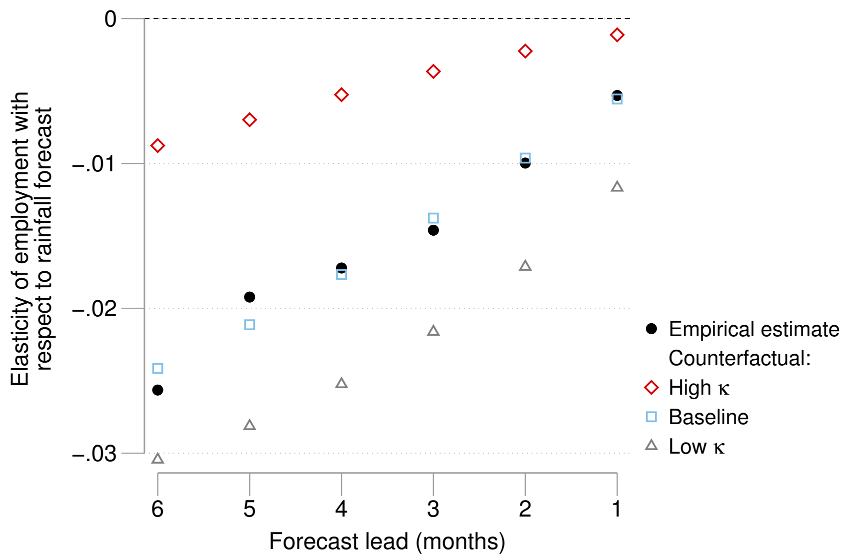
5.3.1 How firm-side adjustment costs drive employment dynamics

Above, we summarized a number of reasons why firms cannot freely or flexibly adjust their labor pool. An advantage of our method is that it captures these costs without imposing assumptions on the *types* of activities that are costly. Rather, it simply infers them from the dynamic pattern of employment responses. How would employment responses differ if the magnitude of adjustment costs was different? What features of the dynamic adjustments help us to infer those costs? How important are the magnitudes of responses, rather than their dynamic pattern, for quantifying these costs? Figure 3 helps answer these questions.

In Figure 3, we compare the empirical, reduced form estimates (from Table 2) with those derived from the calibrated model. Comparing the filled circles (our reduced form estimates from above) with the hollow squares (derived from our baseline calibrations of κ and θ), our model very closely replicates the dynamic responses that we observe in the data.

More interesting, however, Figure 3 also presents simulated dynamics of *alternative* calibrations in which we assume that the firm-side adjustment costs (κ) are ten times larger (hollow diamonds) or one-tenth as large (hollow triangles). Our primary result that responses are monotonically increasing in forecast horizon is generally true across all three calibrations.

Figure 3: Empirical and Model-Based Elasticity Estimates for Construction Employment



Notes: The figure shows coefficient estimates of the effect of rainfall forecasts on construction sector employment from Table 2 compared to the model-derived estimates for the baseline adjustment cost parameters (see Table 3) and the estimates under counterfactual adjustment costs.

However, the magnitudes of these differences matter.

As one would expect, the higher the adjustment costs, the lower the overall level of adjustment that occurs. However the *ratio* of responses to 6-month forecasts compared to 1-month forecasts becomes much larger. With adjustment costs 8 times larger than those we estimate in the data, responses to 6-month-ahead forecasts are eight times larger than the 1-month responses. Compare this to a four-fold difference under our baseline adjustment cost estimates. When adjustment costs are much smaller than our baseline estimates, 6-month responses are less than three times larger than 1-month responses. Thus, the larger are the costs of adjusting, the less overall adjustment there is, but also the greater is the wedge between responses to short-run and medium-run forecasts. This is because as adjustment costs become larger, it becomes more important to spread them out over time. This effect arises from the convex adjustment costs that make large adjustments much more costly than small ones, and it is important for understanding how the burden of adjustment is split between workers and firms in our counterfactuals below.

5.3.2 How the burden is shared between workers and firms

To understand how workers and firms split the costs of productivity shocks, we calculate the firm's present value of profits and the worker's present value of income. We focus on how this present value (PV) changes at time $t-\ell$ when a new forecast of a rainfall shock occurring at time t becomes available. We focus on the PV at the time of the information $(t-\ell)$ to capture the full effect of the rainfall shock as well as any adjustments that occur *before* the rain actually arrives. Our reduced form estimates show substantial adjustment does occur prior to the arrival of rain (between $t-\ell$ and t).

Figure 4 shows how the PV of profits and labor earnings change when news of a rainfall shock becomes available. For both, we present different estimates depending on the firm-side adjustment costs (κ) and the forecast horizon (ℓ).

Panel (a) shows the profit effects. Focusing on our baseline calibration (solid blue circles), a rainfall shock that is forecasted only one month ahead leads to a substantial 0.08% decline in the PV of profits because firms will see a large productivity decline but have limited ability to adjust employment with such short notice. Remarkably, having this information six months in advance instead, they are able to offset almost the entire profit loss via adjustments during those six months.

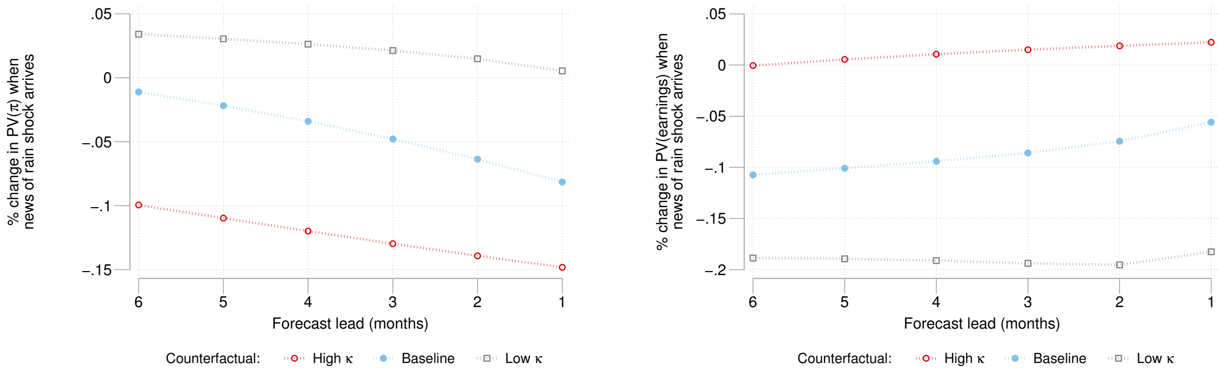
The hollow red circles and hollow gray squares show analogous results for larger and smaller adjustment costs, respectively. When adjustment costs are very large, the profit losses are much more substantial, but interestingly, are less steeply related to the forecast horizon. This is because even at six months, firms ability to adapt to the productivity shock is relatively constrained, and it makes little difference whether the forecast is available six months or one month in advance.[36]

The profit results showed that firms monotonically benefit from longer forecast horizons that afford them more time to adjust, and that more costly adjustment substantially reduces the present value of profits. The primary mechanism of adjustment is through management of their workforce and hiring. For this reason, Panel (b) shows that workers' experience the exact opposite patterns of firms. The longer the forecast horizon, the larger the decrease in the PV of earnings. This is because long anticipation horizons allow the firm to adjust more effectively and pass the costs of the rainfall shock onto workers.[37] In the baseline calibration

[36]When the adjustment costs are low, the present value of firm's profits actually *increase* in response to the shock. In all cases we analyze, the rainfall shock leads to greater scarcity of capital in the economy because construction sector output is crucial to the creation of capital (see Table A5). The market bids up the price of capital in anticipation of this scarcity, which is precisely the present value of profits for firms across the economy. In the cases with larger values for κ, this increase in profits from scarcity is offset by rising labor adjustment costs.

[37]And again mirroring the firm case, when adjustment costs are extremely high, workers are actually slightly *better off* due to a negative productivity shock because their relative price is bid up because of anticipated scarcity.

Figure 4: Change in Present Value of Profit and Labor Value When News About Rain Arrives



(a) Profit

(b) Labor Value

Notes: The figure shows the present value of profit for firms (Panel 4a) and the present value of earnings for workers (Panel 4b) 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 news about the rain shock arrives (time $t - \ell$ in Equations (1) and (2)). For example, the 6-month-ahead forecast effect is the present value from 6 months prior to the arrival of rain.

that matches the data, the lost PV of a 6-month forecast are roughly twice the losses of a 1-month forecast.

This result illustrates that the adjustment cost parameters we estimate to match the data imply that firm-side adjustment costs are larger than the worker-side ones. To see this, note that any agent facing convex adjustment costs values earlier information because it allows her more time to smooth the adjustment and minimize the incurred costs. Indeed, if we dramatically increase the worker-side costs, we see that workers also begin to benefit from earlier information relative to later information (results available upon request). In our context, though, firms' mechanism of adjustment is through layoffs and reduced hiring, both of which shift the costs of the shock onto workers. Despite the fact that workers also face costs of switching sectors, they prefer *less advanced* information because avoiding the costs that firms shift onto them more than outweighs the inconvenience that they themselves face from short notice.[38] In summary then, the fact that the estimates in Panel (b) are upward sloping (less negative at short horizons) is not an inherent feature of our model, but a result that illustrates that demand-side adjustment costs are the key drivers of our results.

[38]These results become even more extreme if workers are myopic. In a sensitivity analysis, available upon request, workers that do not pay attention to expected productivity shocks will not move out of the sector. This dampens overall employment response to the shock but places more of the incidence of the productivity loss on the workers.

5.3.3 Quantifying the costs and benefits of adjustment for the firm

In this setting, firms respond to weather by adjusting their inputs—including labor—in response to news about upcoming shocks. Workers adapt by changing sectors. Adaptation is costly due to rigidity in adjustment, but it also brings benefits in the form of reduced damage from rain shocks. The present values of profit and earnings at the time when news arrives, shown in Figure 4, capture the net effect of both of these channels. In this section, we break down the different sides of adaptation, focusing on costs and benefits for firms.

The pure adjustment costs—the level of κ times the change in hiring in Equation (10)—are straightforward. Changing hiring always comes with a cost, and the size of the change determines the scale of the cost. If a manager wants to adapt to an upcoming shock by making large changes in employment, they either need to pay a high cost for a quick change or spread their employment changes out over time so that they do not climb so high up their convex cost curve. The empirical estimates and model results in Figure 3 show that the magnitude of the employment change grows monotonically with increasing forecast horizon. When assessing the trade-off between higher costs and faster employment changes, the empirical results indicate that managers and firms are deciding that it is worth it to engage in more adjustment if they can spread the costs out over time.

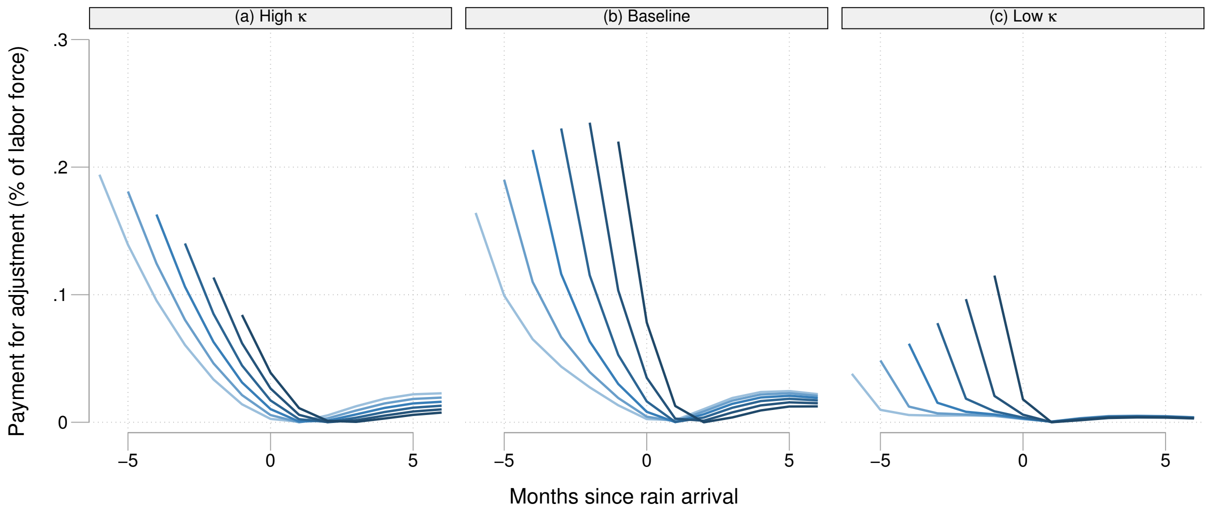
Figure 5 shows impulse responses of the hiring wedge over time. The figure translates the employment changes we see empirically into costs—in units of productivity lost by devoting it to hiring—that the firm pays to adjust its hiring. The figure shows these costs each month leading up to, during, and after a rainfall event. The lines show costs for different forecast horizons, and the panels (a, b, and c) show the value for high, baseline, and low values of κ respectively.

One can see that in the baseline (panel b), firms find it worthwhile to pay substantial adjustment costs at all forecast horizons, a result that is reflected in the employment changes in Figure 3. For larger adjustment costs, firms want to adjust their labor force, but high costs prevent them for making as substantial of changes, particularly at short forecast horizons. Within the horizons we investigate, labor adjustment and cost rise monotonically every month in this high cost-case. In a world with high κ, relatively surprising rainfall events would see very little labor force adjustment and a low cost paid for adaptation. This is precisely because it would not be worthwhile to engage in such costly behavior.

In panel (c), one can see that there is also little cost paid for adjustment when κ is low, but now it is despite a large change in the labor force. Firms get a high “bang for their buck” when adapting to a shock if adjustment is cheap.

Together, these figures tell an important story for climate adaptation and estimation of climate damages. If the world is one with high costs of adjustment, like the high κ case here, then people will not engage in much adaptation, and researchers will not find

Figure 5: Isolating the Adjustment Cost Wedge for Firms

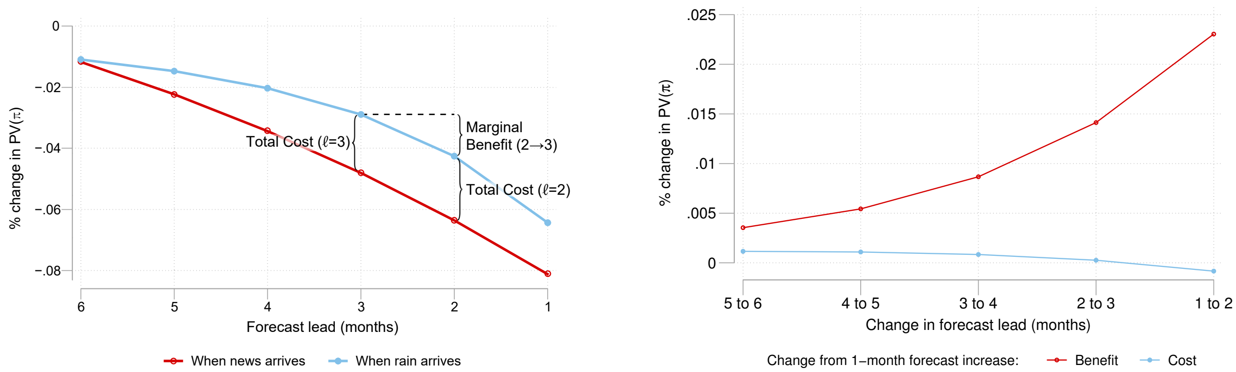


Notes: The figure shows impulse responses of the share of the firm's labor force devoted to hiring as in Eq. 10 (in units of percent of their labor force). The panels show costs each month from 6 months prior to the arrival of rain until 6 months after. The lines are at different forecast horizons, with the lightest colored lines at the 6 month horizon and the darkest colored lines at the 1 months horizon. The three subpanels show how these costs differ by firm-side adjustment cost parameter, κ.

substantial evidence for adaptation in the empirical record. Firms would want to engage in adaptation in this case if better information was available or if shocks were highly persistent, but high adjustment costs simply prevent them from taking action in many cases. Models and empirical analyses that rule out *ex ante* adaptation are conducting analysis as if the adjustment costs are infinite. The low κ case will be one with a high quantity of adaptation and a low cost of adaptation. In this case, damages estimates that ignore *ex ante* adaptation might miss a substantial part of the story. In between these two extremes, *ex ante* behavior is important to take into account both in terms of the quantity and cost of adjustment.

The direct adjustment costs are only part of the adaptation cost story. Prior to the arrival of rainfall, firms are also affected by changes in labor supply as well as spillovers from sectoral linkages and trade. The complex interaction of these different factors can be summarized by comparing the present value of profit for the firm at the time when rainfall arrives (time t) versus at the time when news about rainfall arrives ($t - \ell$). The difference in these values captures the effect on firms of the myriad *ex ante* adaptation actions engaged in both by construction firms and by all other market participants. Figure 6 Panel 6a shows this difference for the baseline calibration. The top line is the present value of profit when rain arrives, and the bottom line is the present value of profit when news arrives. The vertical difference between these two lines captures the total "cost" of actions taken before the rain shock realizes.

Figure 6: Benefit and Cost of Adapting Given 1-month Change in Forecast Horizon



(a) Calculating adaptation costs and benefits using profits

(b) Costs and benefits from 1-month forecast horizon changes

Notes: Panel 6a shows the present value of profit for firms as a function of the forecast horizon for the baseline calibration. The blue line with solid circles shows the present value when rain arrives (time t). The red line with hollow circles shows the present value when news arrives (time $t - \ell$). Both lines use the same discount factor. The vertical distance between the lines is the cost of all actions taken prior to the arrival of rain. The distance between two points on the time t line is the "marginal" benefit of a 1-month increase in forecast horizon. Panel 6b shows the marginal cost and marginal benefit values for each forecast horizon in our sample.

Comparing two points along the blue line, one can also estimate the benefit of improving the forecast horizon. As we discussed in the previous section, firms benefit more from information available further in advance by spreading the adjustment over a longer period, allowing them to engage in more adaptation at a lower cost. We refer to the difference between two points along the top curve as the "marginal" benefit of forecasts because it is the reduction in damage provided by a 1-month increase in the forecast horizon.

Finally, Panel 6b shows the marginal benefit of forecast horizon changes in the top curve (red with hollow circles) and the marginal cost of adjustment in the bottom curve (blue with filled circles). The marginal cost is the difference in costs between two forecast horizons, as indicated on the x-axis. One can see that for all forecast horizons, the benefit of a 1-month increase in forecast horizon is greater than the cost. In fact, due to spillovers across sectors and changes in labor supply, marginal costs are actually negative for firms at the shortest forecast horizons. Marginal benefit and cost converge for longer horizons. If firms were able to choose their forecast horizon (and if forecasts were costless for them to produce), they would choose a longer horizon than the longest we consider here. The model estimates that firms currently pay 10% of typical monthly profit to adjust to a rainfall shock that is anticipated only 1 month in advance. They pay more—13%—for adjusting to a 2-month-ahead forecast, but they also gain more in terms of reduced losses once rain arrives. For longer horizon forecasts, they pay substantially less. When given 6 months advance notice, firms pay only 0.5% of monthly profit to adjust.

5.4 Future climate projections

Unless greenhouse gas emissions are brought down substantially, future changes in the climate are projected to increase the volatility of rainfall around the world. The most recent, comprehensive climate projections under the high climate forcing scenario (CMIP6 SSP5-8.5) indicate that the standard deviation of rainfall will rise 12%, on average, in the continental U.S. between now and the end of the century (O'Neill et al., 2016). The rainfall distribution is bounded below by zero, so this increase in volatility will lead to a higher probability of heavier rainfall. Figure 7 shows rainfall volatility projections for every year between now and 2100.[39]

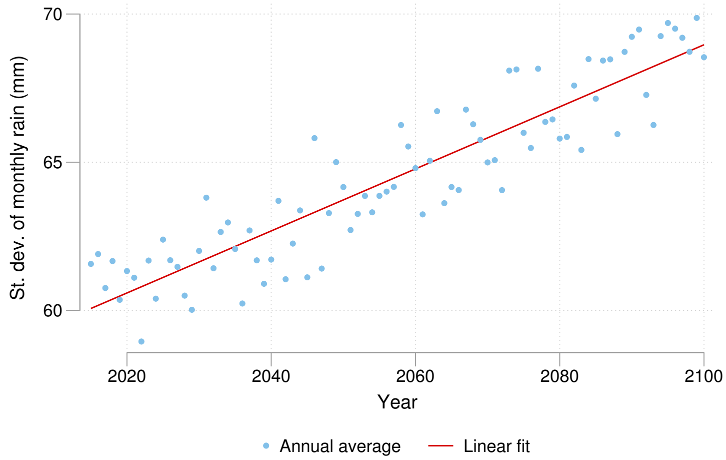
Greater rainfall volatility will have two effects in our model. First, any shock—whether positive or negative—will require costly adjustment to either avoid damages or to take advantage of benefits. For firms, these costs are the hiring wedge in Equation (10) and shown in Figure 10. Second, there will be a higher probability of larger rainfall shocks conditional on one occurring, and as discussed above, this is particularly salient for rainfall which is bounded above 0.

The results in previous sections give the effects of a one standard deviation increase in rainfall on employment, productivity, profit, and earnings. If the standard deviation of rainfall increases from about 62 mm per month today to about 70 mm per month by 2100, how will that affect the construction industry and labor market? Simply extrapolating from our current estimates, holding everything else fixed, this will result in an additional loss in value added for the construction sector from a typical rainstorm of 0.024 percentage points. This magnitude might appear small, but we emphasize that is the loss, over-and-above losses already incurred in the current climate, from routine month-to-month rainfall. Given a total value added for the construction industry in the U.S. of roughly $1 trillion per year (BEA, 2019), an increase in losses of this magnitude could translate into tens of billions of dollars of damage to the economy.

Our estimates are that profit for construction firms will change by a similar magnitude, with firms losing around 0.01 percentage points more in present-value profit from a typical rain storm. By comparing profit losses in the baseline scenario (shown in Figure 4) and profit losses under projected climate change, we can estimate the change in forecast horizon necessary for a firm to offset this impact.

[39] Figure A9 shows the projected standard deviation increase after residualizing on location and month-of-year fixed effects. The growth in volatility is the same.

Figure 7: Projected monthly rainfall standard deviation for the continental U.S.



Notes: The figure shows the projected standard deviation of monthly rainfall (in mm) each year from the present until 2100 in CMIP6 SSP5-8.5. Each point is the month-to-month standard deviation of rainfall for each grid point in the CMIP6 projections averaged across the continental U.S. The raw standard deviation is debaised to match the sample average from our estimation sample.

Profit losses get smaller as firms can plan further ahead. To gain enough flexibility to avoid the projected extra profit loss, firms would forecasts to arrive just over half-a-month further in advance. In other words, a firm that faced a 12% larger rainfall event would be left no worse off it it was also given a half-month-further-ahead forecast. So one way to think about the climate damages that we estimate is that firms would need to find a way to increase their planning horizon by 50%, if they are currently planning one month ahead, in order to offset the damage from a 1 standard deviation increase in rain.[40]

For longer baseline forecast horizons, the size of the increase falls. Figure 4 shows that at longer horizons, firms are able to largely avoid profit losses, so smaller forecast horizon increases are sufficient to avoid extra damages under projected climate change. Planning at such long horizons is inherent challenging, however, so a small increase in forecast horizon might still be hard to achieve. Figure A11 shows the forecast horizon improvement needed to offset projected profit losses for each of the forecast horizons considered in the paper.

Long-range weather forecasting has been an area of focus for climatologists and meteorologists, particularly since the early 1990s. Some success has been achieved in forecasts at a monthly or seasonal horizon. The use of ENSO signals to forecast seasonal rainfall

[40]In practice, our results indicate that firms are planning all the way out to a 6-month horizon, so this comparison is just illustrative.

and temperature, which we exploit in this paper, is one of the clearest success stories. But such forecasts are inherently difficult, and barring improvements to existing forecasts, more careful attention by construction project managers, or other adaptations to reduce rigidity in the labor market, the increased volatility projected by climate models will translated into economic costs.[41]

Losses stemming from the interaction of labor adjustment costs and weather volatility constitute damages from climate change that are, as far as we are aware, novel in the climate economics literature. The damages do have an important antecedent in earlier work that emphasized the role of capital and agricultural input adjustment costs in overall climate damage (Quiggin and Horowitz, 2003, Kelly et al., 2005). The focus of that work, however, differs from ours in an important way: they focus on the costs paid along the transition path between equilibria while we focus on adjustment costs paid due to routine weather shocks. Thus, one could distinguish between the "transition costs" pointed out by the previous literature and the "adjustment costs" that we investigate. Adjustment costs and attendant damages are important because they are paid routinely. Indeed, every time a weather shock realizes the economy either pays adjustment costs or suffers damage from the change (even if counterfactually from not adjusting to capture a gain from beneficial shocks).

6 Conclusion

Climate change is expected to cause substantial damage to the global economy. Our understanding of that damage comes primarily from integrated assessment models (IAMs) that estimate the equilibrium response to a change in the climate or from microeconometric estimates of the acute effects of weather. Both of these sources overlook important dynamics. In this paper, we identified two understudied aspects of the economics of climate change where dynamics play an important role: labor market adjustment and the effects of rainfall volatility. We focused on these issues in construction, an economically important, climate exposed industry that has itself been largely overlooked by previous research.

We found evidence that construction labor markets respond sluggishly to forecasts of rainfall shocks—an indication that market participants face adjustment costs. Empirically, unexpected rainfall is associated with little change in construction employment. Rainfall that can be anticipated well in advance, in contrast, leads to large changes in employment. Calibrating a multi-sector model labor market model, we found that the labor market responses to forecastable rainfall imply large labor adjustment costs.

Adjustment costs are a source of climate damage, a reason for *ex ante* adaptation by

[41] Toth and Buizza (2019) summarize the history and possible future efforts to achieve gains in monthly, seasonal, or even longer-horizon forecasts. More pessimistically, Scher and Messori (2019) have recently argued that climate change might make rainfall forecasting even harder in the future.

market participants, and a limit to the adaptation process. Given the adjustment costs we estimate, weather shocks cause not only acute damage, but also involve substantial payment for adaptation. Existing methods that estimate the effects of weather on economic outcomes will miss this source of damage. Increases in weather volatility—which is already apparent in the recent historical rainfall record and is projected to continue under unmitigated climate change—will also imply higher climate damage due to more frequent or larger need for adjustment. This source of damage is overlooked by IAMs. In our context, both of these effects strengthen the case for public policy to reduce the emissions of climate pollutants.

For an individual firm facing a world of increasing climate volatility and costly adjustment, we showed that implementing improvements to the hiring process that bring down the cost of employment adjustment can substantially offset the negative effects of weather variation. Firms can also take action to better incorporate longer-horizon information into their decision-making. For construction firms that must make multi-month contracts based on weather expectations, investing in innovations and process improvements that will allow this type of planning will be of high value to improve flexible and resilience in the face of a changing climate.

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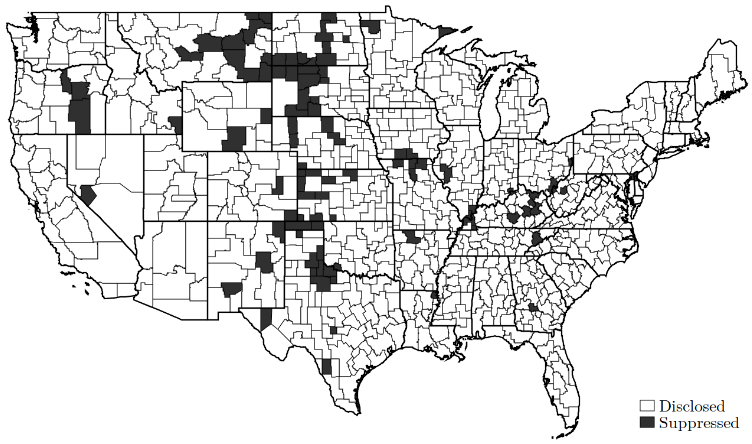
Adjusting to Rain Before It Falls

Downey, Lind, Shrader

Appendix for online publication

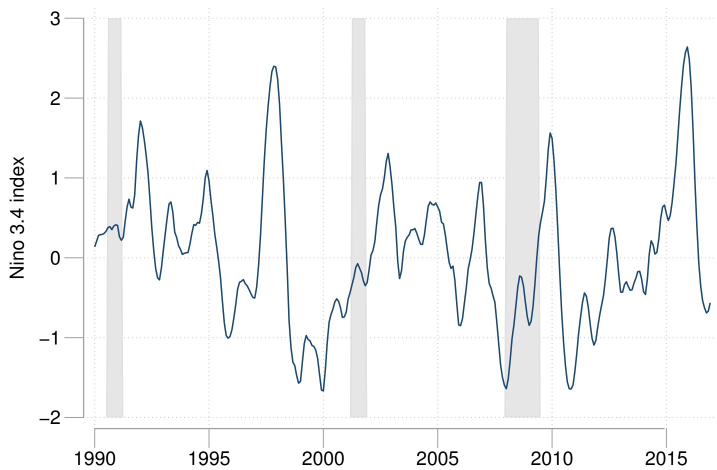
A Supplementary figures and tables

Figure A1: Commuting Zones Where Construction Employment is Disclosed



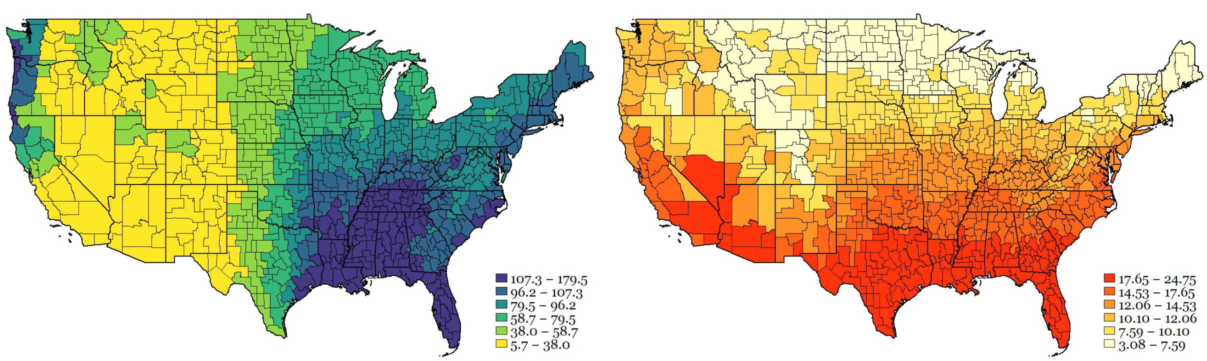
Notes: The map shows commuting zones in the continental U.S. where construction employment is disclosed (white) versus suppressed (black) for all months in our sample.

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

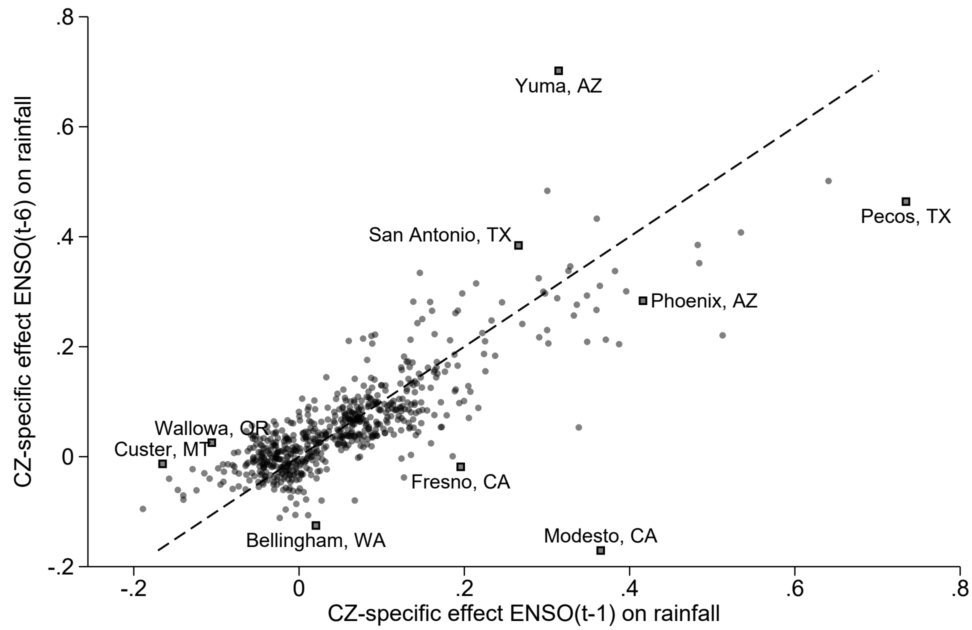


(a) Pop. weighted precipitation

(b) Pop. weighted avg. temperature

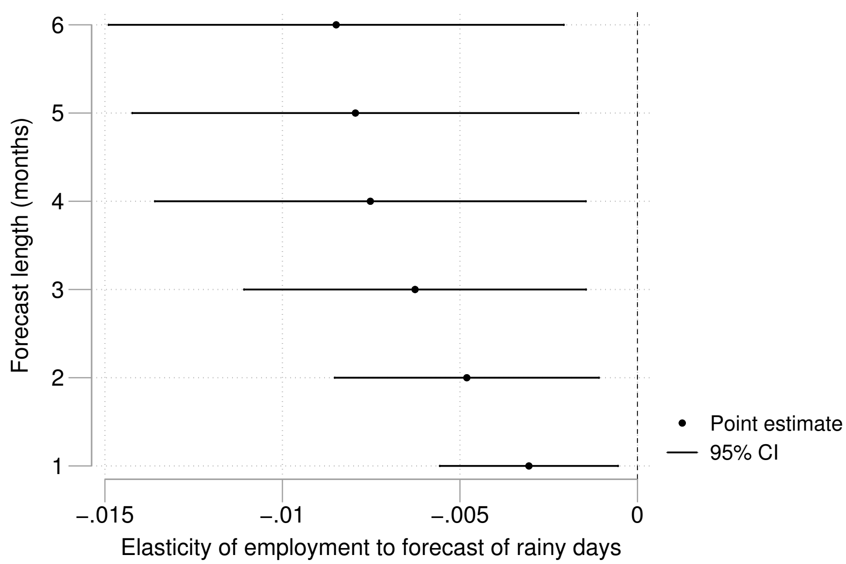
Panel (a) shows the time series average across the full sample (1990 to 2016) of population weighted monthly total precipitation (in mm) in each commuting zone. Panel (b) shows the population-weighted average temperature (in °C) for each commuting zone over the same period.

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



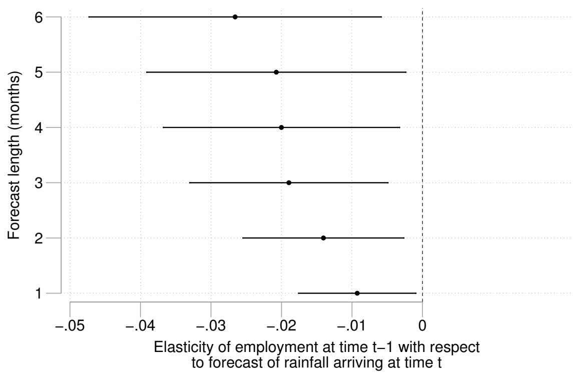
Notes: The figure shows coefficient estimates from Equation (1) for 1 and 6-month ahead predictions of the rainfall using ENSO. Example locations where the predictions at the two horizons differ substantially are labelled. The dashed line is a 45° line.

Figure A5: Main Results Using Rainy Days

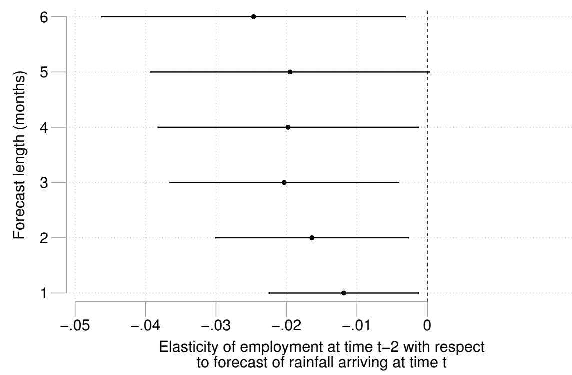


Notes: The figure shows coefficient estimates from Equation (2) for rainfall predicted 1 to 6 months ahead. Predictions are based on CZ-specific responses to changes in the ENSO. In our primary specification (see Table 2), the core independent variable is the log number of millimeters of precipitation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

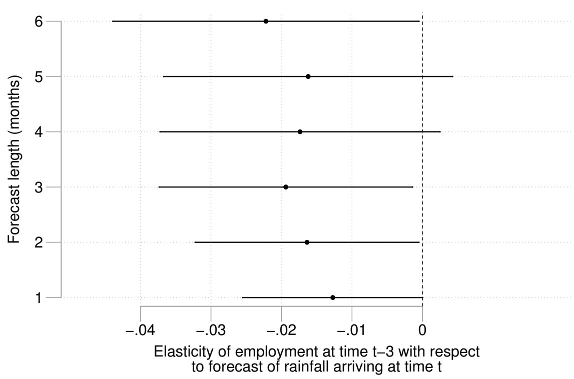
Figure A6: Effect of Rainfall Forecasts on Employment Prior to the Arrival of the Rain Shock



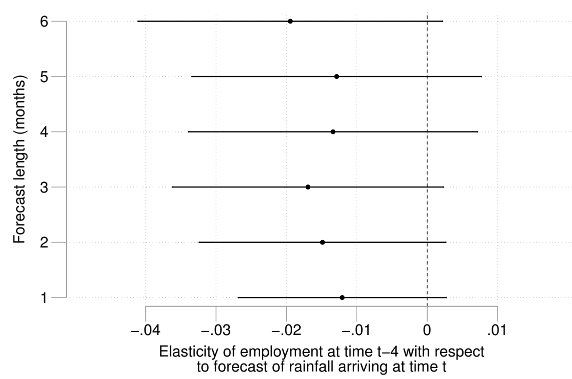
(a) $h = 1$



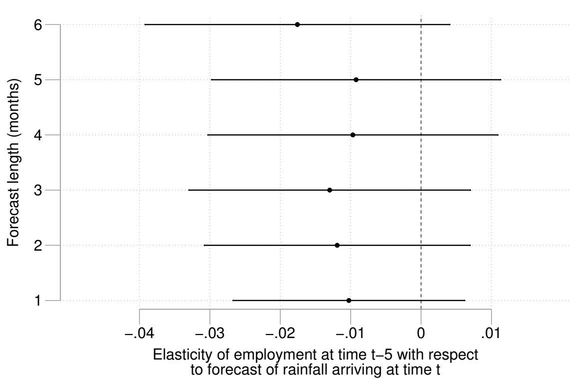
(b) $h = 2$



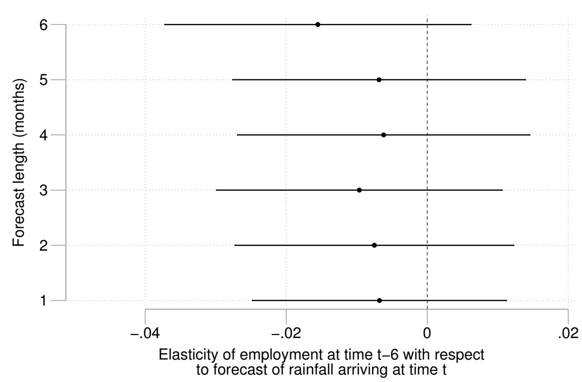
(c) $h = 3$



(d) $h = 4$



(e) $h = 5$



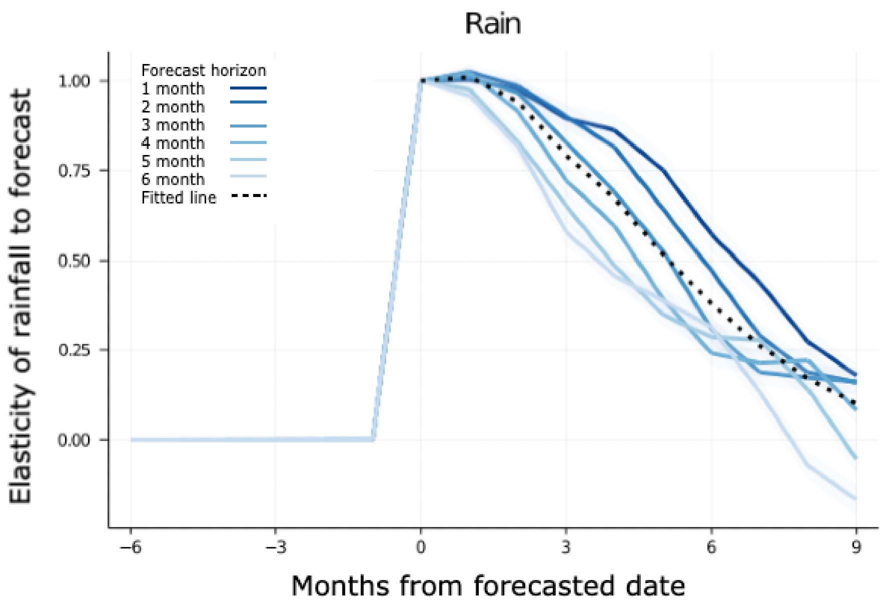
(f) $h = 6$

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.

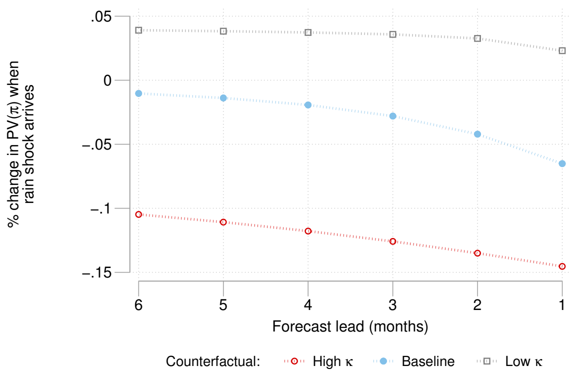
Table A6: Employment Statistics (Calibration target for $\omega_{ii'}$)

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

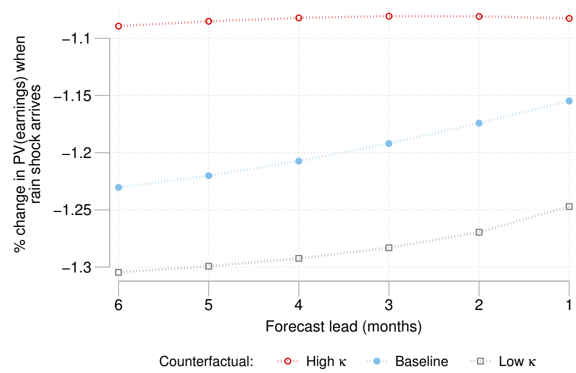
Notes: The second column reports total share of workers by sector (industries or non-employment, CPS). The entries on the right show the share of these workers moving from that sector to each other sector per month in the current population survey (CPS). NAICS codes associated with the listed sector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

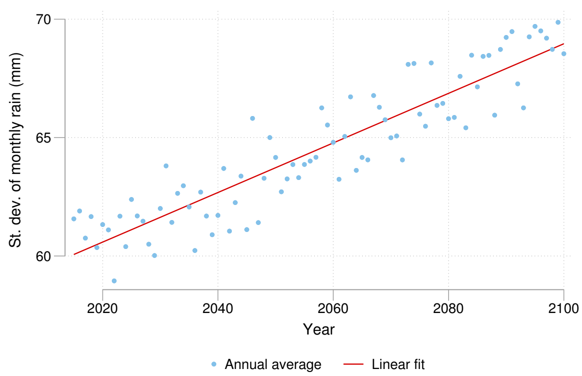


(b) Present Value of Earnings

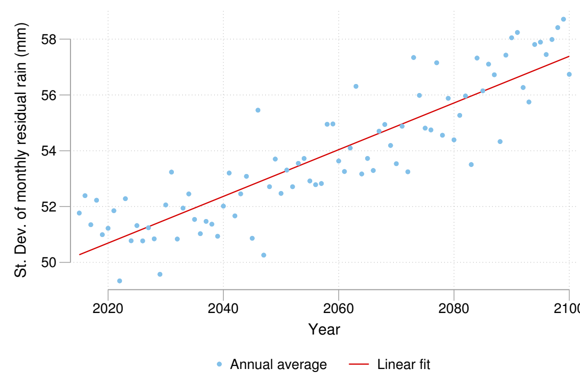
Notes: The figure shows the present value of profit for firms (Panel A8a) and present value of earnings for workers (Panel A8b) as a function of the forecast horizon and three different values of the firm-side adjustment cost parameter, κ: high (red with hollow circles), baseline (blue with filled circles), 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.

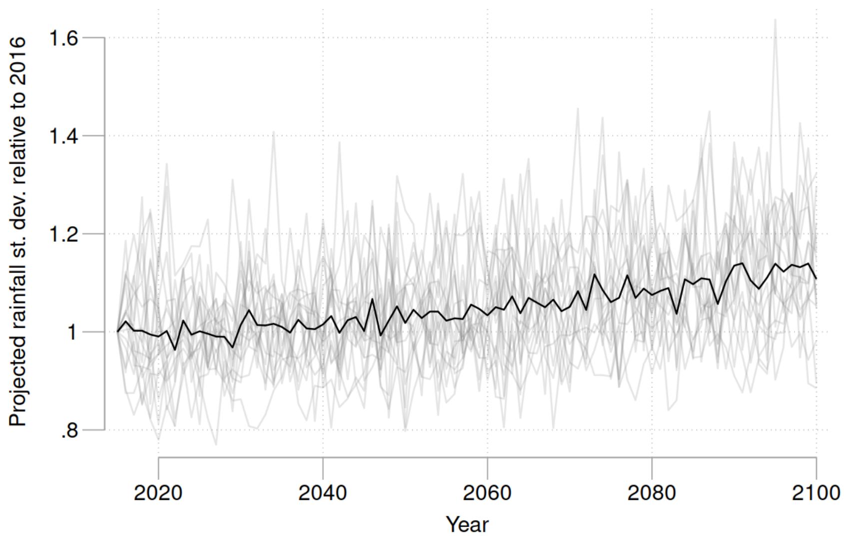


(b) Residual std. dev.

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.

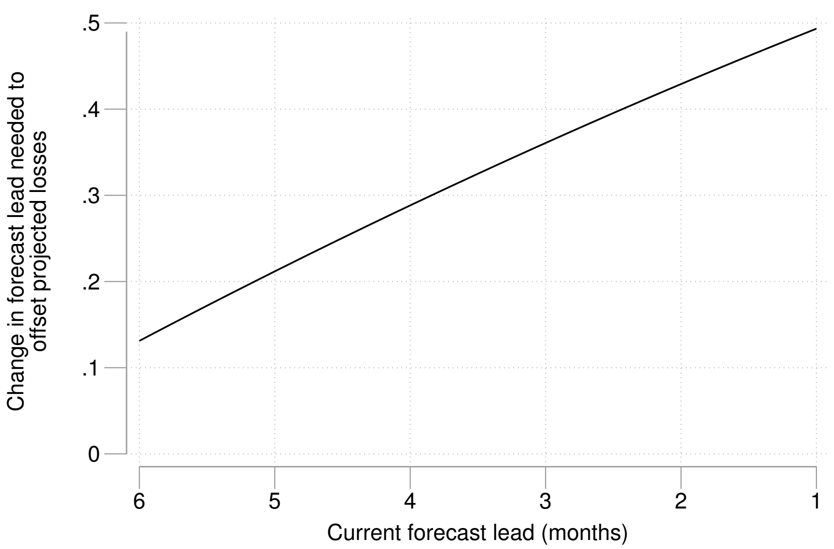
E Model Robustness Checks

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	$\frac{\partial \ln \kappa_i}{\partial \ln \bar{W}_i} = .1$	$\frac{\partial \ln \kappa}{\partial \ln \bar{W}_i} = 1$	$\kappa_i = 0$ 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.