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Sylvain Leduc and Daniel J. Wilson
Federal Reserve Bank of San Francisco

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Climate Change and the Geography of the U.S. Economy*

Sylvain Leduc[†] Daniel J. Wilson[‡]

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Abstract

This paper examines how the spatial distribution of people and jobs in the United States has been and will be impacted by climate change. Using novel county-level weather data from 1951 to 2020, we estimate the longer-run effects of climate on local population, employment, wages, and house prices using a panel polynomial distributed lag (PDL) model. This model and the long historical data help capture important aspects of local climate changes, such as trends in temperature. The historical results point to long-lasting negative effects of extreme temperatures on each of the outcomes examined. A long lag structure is necessary to appropriately capture the longer-run effects of climate change, as short-run effects are small. Using county-level weather projections based on alternative greenhouse gas emissions scenarios, we use the estimated models to project the spatial distribution of these local economic outcomes out to 2050. Our results point to substantial reallocations of people and jobs across the country over the next three decades, with mobility increasing by between 35 and nearly 100 percent depending on the scenario. Population and employment are projected to shift away from the Sunbelt and toward the North and Mountain West.

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[†]Federal Reserve Bank of San Francisco, sylvain.leduc@sf.frb.org

[‡]Federal Reserve Bank of San Francisco, daniel.wilson@sf.frb.org

1 Introduction

"We see nothing of these slow changes in progress, until the hand of time has marked the lapse of ages...."
– Charles Darwin (1859), *The Origin Of Species By Means Of Natural Selection.*

In his groundbreaking treatise, Charles Darwin discussed the empirical challenges of studying evolution given its glacial pace in relation to a single human lifespan. Similarly, many scholars of today have argued that the slow pace of historical climate changes have hampered efforts at estimating their effects, whether environmental, social, or economic. For instance, Carleton & Greenstone (2021) recently wrote, "Because the climate has remained stable throughout modern human history, it is difficult to isolate experimental variations in the long-run climate." This has led many researchers to rely on calibrated structural models (e.g., Cruz & Rossi-Hansberg (2021), Rudik et al. (2022), and Bilal & Rossi-Hansberg (2023)) or to infer longer-run climate change effects from estimated short-run weather effects (e.g., Dell et al. (2012), Burke et al. (2015), Deryugina & Hsiang (2017), Colacito et al. (2019) and Rudik et al. (2022)).[1]

Yet the notion that there is empirically insufficient variation in climate in modern history is becoming increasingly untrue. In the United States, for instance, long historical weather readings reveal clear evidence of climate changes over the past several decades. Moreover, the type, magnitude, and even direction of climate changes have varied widely across the country. For instance, as we document in the paper, the number of extreme heat days per year has increased substantially since 1951 in much of the South, but it has fallen slightly in the Midwest. Over the same period, the number of extreme cold days per year has fallen substantially in the Northeast, the Upper Midwest, and the Mountain West regions. Precipitation patterns also have changed substantially, increasing in the Northeast but decreasing in much of the West.[2]

In this paper, we take advantage of recently released detailed historical weather data across U.S. counties to examine how the spatial distribution of people and jobs, along with wages and house prices, has been and will be impacted by climate change.[3] The new data set from the National Oceanic and Atmospheric Administration (NOAA) contains daily county-level temperature and precipitation measures from 1951 to the present. We use these daily data to construct annual measures of the within-year temperature distribution for each county along with annual precipitation variables, and we combine these with annual county data on population, employment, wages, and house prices going as far back as 1969.

[1]Throughout the paper, we use the term "longer run," as opposed to "long run," to describe the horizon over which we estimate historical and projected impacts of climate changes because both the changes themselves and the impacts are likely to last longer than thirty years, which is our maximum horizon of analysis.

[2]These patterns are documented in Figures 1 and 2.

[3]Throughout the paper, we use the term "climate change" to refer to the global phenomenon of rising temperatures and shifting weather patterns, while we refer to the local climatic manifestations of this phenomenon as "climate changes."

Exploiting the substantial geographical and temporal variation in these data, we estimate the historical short- and longer-run effects of climate change using a panel polynomial distributed lag (PDL) model. The combination of a long time-series of local weather and the PDL model allows us to examine how each economic outcome is impacted by local climate changes. Local climate changes for each of several weather variables are captured by three moments: the mean over the prior 30 years, which is the standard definition used by climatologists for a climate "normal"; the trend over the prior 30 years; and the acceleration or deceleration in the trend. Thus, our approach allows us to focus on measures of *climate change* instead of relying on short-run variations in *weather* to identify climate change effects, as is done in most of the literature.

We then combine these estimates with county-level weather projections out to 2050 to estimate the impact of projected climate change on the spatial distribution of population, employment, wages, and house prices over the next 30 years.

Using our PDL model, we estimate significant medium- and longer-run effects of weather shocks on population growth and employment growth, as well as on wages and house prices. These results point to mobility – both of households and jobs – as an important channel of climate change adaptation in the United States. Importantly, we show that failing to include long lags of weather, as in much of the prior literature, implies much smaller effects on population and employment and the misperception that adaptation via mobility is limited. We obtain very similar results at the commuting zone level, indicating that the effects are driven by reallocation across labor markets rather than commuting patterns within labor markets.

Using a simple graphical analysis, we also show these relationships are present in the raw data. Looking across counties, both mean-shifts and trend-shifts in the annual number of extreme heat days over the prior 30 years are strongly negatively correlated with subsequent longer-run population growth and employment growth. Our formal estimation of the effects of climate change on local population, employment, wages, and house prices using the panel PDL model confirms and quantifies these relationships.

The economic responses we estimate reflect different channels of local adaptation. Local areas experiencing climate changes may adapt both *ex-post* and *ex-ante* to climate change. Ex-post adaptation is *reactive*, reflecting direct and indirect responses of agents to past weather shocks. For instance, households and firms may move away from areas suffering from drought as a result of numerous prior years of high temperatures and low precipitation. Ex-ante adaptation is *proactive*, reflecting responses of agents that, looking forward, anticipate future changes in the probability distribution of weather and adapt now in advance of those expected changes. In either case, adaptation can occur through a variety of channels. For instance, local firms and governments may invest in more resilient infrastructure, and households and businesses may accumulate precautionary savings to smooth out the impact of unforeseen extreme weather events. Some households and firms may simply move away from places where the climate is expected to worsen toward places where it is expected to improve (or worsen less). We show that our empirical model we can account for both ex-post and ex-ante adaptation to the extent that agents have adaptive expectations.

To help interpret our results, we present a simple spatial equilibrium model that illustrates the role of amenities and productivity in determining how local climate changes can impact economic outcomes. It also highlights the important role of the elasticity of housing supply in amplifying the responses of house prices, which dampens (without eliminating) the migration response. That is, the supply of housing in places with comparatively better climates for living only partially adjusts over the longer-run in response to increased demand, putting upward pressures on house prices, which tends to moderate migration to those areas. The model thus ascribes the population outflow from regions hit by adverse climate changes to some combination of reduced amenities and reduced productivity, which also lowers wages and employment. Guided by the model, we estimate that the impacts of climate change on amenities and productivity are both quantitatively important channels underlying our empirical findings.

Combining the estimated panel PDL model with projections of local climate changes, we project substantial reallocations of people and jobs across the country over the next three decades. Hotter counties in the Sunbelt are predicted to lose both population and employment relative to the North and the Mountain West.

These results are *a priori* surprising given evidence of past migration toward warmer climates in the United States (Rappaport (2007), Partridge (2010)). However, we first show that our projections would actually represent a continuation and acceleration of a pattern since at least the 1980s, whereby the cross-county correlation between population growth and hot climates has turned from strongly positive to slightly negative. Conversely, the cross-county correlation between population growth and historically cold climates has turned from strongly negative to zero, and it is projected to become strongly positive. Going forward, these projections point to an increasingly negative correlation between counties with relatively hot climates and population growth. A natural interpretation is that, as the relatively hotter places in the U.S. experience more extreme heat days (and higher temperatures on those days) and the relatively colder places experience fewer extreme cold days (and higher temperatures on those days), households are shifting from relatively attractive to relatively unattractive places in which to live and work.[4] This result holds even if one excludes large Sunbelt cities, which have experienced both substantial increases in annual extreme heat days and rapid, but slowing, population growth over the past 70 years.

In terms of aggregate magnitude, we estimate that climate changes will increase population reallocation over 2021–2050 by 35, 75, or roughly 100 percent, depending on the climate change scenario.[5] We estimate similar impacts of climate changes on the aggregate amount of employment reallocation, between roughly 30 and 100 percent, depending on the scenario. In contrast, we also

[4]This interpretation is consistent with evidence that extreme heat reduces subjective well-being (Baylis et al. (2018)) and increases suicide rates (Gammans (2020)).

[5]We measure population reallocation by the mean absolute deviation (MAD) between county population growth and national population growth, where growth is measured as the 30-year change in log population from 2021 to 2050.

show that relying on a static empirical model that abstracts from long lags of weather would vastly underpredict the degree of economic mobility.

Our results provide direct empirical evidence for mobility – both of households and jobs – as an important channel of climate change adaptation in the United States. This suggests mobility likely will be an important factor determining the impact and welfare costs of climate change in the decades ahead, as argued, for instance, by the U.S. Environmental Protection Agency (2017), Carleton & Hsiang (2016), Desmet & Rossi-Hansberg (2015), and Partridge et al. (2017). Importantly, we find that the longer-run effects of weather on local population growth has been stable over the past four decades, suggesting that despite the decline in U.S. mobility rates (see, for instance, Jia et al. (2023)), mobility responses to climate changes have not declined.

In extensions to our baseline analysis, we also allow marginal weather effects in our PDL model to be heterogeneous across counties, varying with counties' historical climates (historical mean of each weather variable), incomes (historical mean of income per capita), and climate change beliefs (using the Yale Climate Survey). First, we find that the longer-run negative effects of weather variables (extreme temperature days and precipitation) are driven by poorer counties. These variables have a positive longer-run effect, if anything, in richer counties, consistent with relatively greater adaptive investments in richer counties. Second, we find that the longer-run negative effects of extreme temperatures and extreme precipitation are worse for places unaccustomed to them, consistent with adaptation to historical climates. Third, we find suggestive evidence that the negative economic effects of climate changes are largest in places with more skeptical attitudes toward climate change.[6]

It is also important to acknowledge that our paper focuses only on climate changes related to local temperature and precipitation. Local temperature and precipitation are the proximate causes of many important weather-related events such as floods, droughts, wildfires, heat waves, and cold spells and hence longer-run changes in local temperature and precipitation will largely capture changes in these climate risks. However, there are other potentially important place-varying aspects of climate change, such as sea-level rise, that are driven by global rather than local changes in climate. That said, the same methodology used in this paper could be used in future research to study the effects of factors like sea-level rise on economic geography given sufficient historical, spatially disaggregated data.

2 Contributions Relative to Prior Literature

Our use of long-lagged distributed lag models offer potentially important advantages over prior approaches. These prior approaches generally fall into three strands. One strand seeks to identify the effect of climate changes on economic outcomes using purely cross-sectional, geographic variation in

[6]This result could also reflect adaptation: places where residents believe in climate change are more likely to have made adaptive investments (personally or via their local governments) compared with residents of climate-change-denying places.

climate "normals," which are simply long historical averages of observed weather (see, for example, Mendelsohn et al. (1994), Schlenker et al. (2005), and Nordhaus (2006)). A natural concern with this approach is the likely correlation across geographies between climate normals and unobserved local characteristics (fixed effects) that also affect economic outcomes. Auffhammer et al. (2013) provide a survey of that literature and contrast it with a second strand, which uses higher frequency (e.g., daily, monthly, yearly) panel variation and typically includes geographic fixed effects.[7] They note that "[t]he econometrician's choice of a weather versus a climate measure as an explanatory variable critically affects the interpretation of the estimated coefficients in the econometric model: that is, whether the outcome is a true climate response or a short-run weather elasticity."

A number of recent studies in the second strand, relying on higher frequency panel variation, have put forth an envelope theorem argument to infer long-run responses to climate changes based on estimated short-run weather elasticities (see, for example, Deryugina & Hsiang (2017) and Rudik et al. (2022)). As stated by Rudik et al. (2022): "The envelope theorem implies that *for an optimized variable*, variation in weather is isomorphic to variation in climate" (italics added). The obvious appeal of this approach is that it does not require long historical within-place data on weather to capture climate changes. Rather, it only requires within-place data on weather fluctuations.

However, the envelope theorem approach requires strong assumptions. Clearly, it would not apply to outcomes that households or firms do not optimize. However, even under complete optimization, Lemoine (2021) demonstrates that the the envelope theorem approach requires the optimization problem to be static.[8] In contrast, by exploiting the observed long histories of weather, our approach does not rely on these strong assumptions associated with the envelope theorem.

A third strand of the literature was pioneered by Burke & Emerick (2016) who, like Deschênes & Greenstone (2007) and Lemoine (2021), argue that short-run weather effects likely differ from longer-run effects because of the types of adaptation behavior mentioned above. They proposed estimating a cross-sectional regression using long-differences – i.e., changes in weather and economic outcomes

[7]Prominent examples of this approach include Deschênes & Greenstone (2007), Dell et al. (2012), and Colacito et al. (2019), which estimate the impact of temperature or other weather "shocks" on economic outcomes over the short run. Some papers in this literature extrapolate from short-run effects to project very long-run impacts from projected climate changes (e.g., Burke et al. (2015)). Yet, as Deschênes & Greenstone (2007) point out, a "primary limitation to this approach is that farmers [agents] cannot implement the full range of adaptations in response to a single year's weather realization. Consequently, its estimates may overstate the damage associated with climate changes or, put another way, be downward-biased." In other words, adjustment costs can cause short-run responses to weather shocks to differ from longer-run responses.

[8]Consider two examples. First, consider a farmer experiencing an abnormally dry year. Their optimal response to that precipitation shock may depend on prior years' precipitation shocks. If precipitation was high in prior years, the farmer can draw from local groundwater and reservoir reserves to irrigate as usual. However, if precipitation was low in prior years, local water reserves could be depleted, forcing the farmer to adapt by changing irrigation practices or crops. As a second example, consider the residential location decision of a household, which underpins the spatial distribution of population. Local wildfire risk depends heavily on the precipitation and temperatures in past years. Like water reserves, wildfire risk (or its inverse) can be thought of as a history-dependent resource stock. In both examples, a hot and dry year imposes a cost that carries over to future years because of its effect on a resource stock. More generally, many types of weather shocks can affect public and private capital stocks and hence affect future behavior of households and firms.

over long periods of time. The long-differencing removes geographic fixed effects, as would first (year-over-year) differencing or mean-differencing (the conventional fixed effects estimator). The long-difference estimator has an intuitive appeal in that it places greater weight on low-frequency variation compared with first- or mean-differencing. However, as demonstrated in Lemoine (2021) and further highlighted in Section 3 below, it still omits the effects of both long-lagged weather shocks (ex-post adaptation) and expectations of future weather (ex-ante adaptation).

We argue that our approach, using a long-lagged PDL model, combines the advantageous features of the first two strands, exploiting variation in climate (as opposed to weather) and including fixed effects (made possible by sufficiently long historical data).

Ours is not the first paper to employ a distributed lag (DL) model to study environmental or climate issues. In their cross-country study of the impact of annual temperature fluctuations on GDP growth, Dell et al. (2012) include results from a DL model with up to 10 lags. They find negative contemporaneous effects of average annual temperature for poorer countries, though not for high-income countries, and they uncover little evidence of lagged effects. By contrast, across U.S. counties, we find substantial longer-run weather effects on economic activity that often differ in magnitude and direction from the contemporaneous effects. Hsiang & Jina (2014) also use a DL model, with 20 years of lags, in their study of the longer-run effects of cyclones. They find negative effects of cyclones on national income per capita that are modest in the short-run but large in the longer-run. In concurrent work, Bilal & Rossi-Hansberg (2023) also use a panel DL model in their study of spatial climate change effects in the U.S. since 2000. Their empirical analysis differs from ours in a number of ways. Most importantly, they analyze the impacts of discrete, extreme weather events whereas we examine the effects of shifts in the yearly distribution of daily temperature and precipitation. These shifts, such as gradual increases in the number of very hot days in a year, not only increase the likelihood of extreme weather events, but also impact local areas' amenities, productivity levels, and other fundamentals even absent changes in extreme events.[9] Kahn et al. (2021) and Mohaddes et al. (2022) use panel DL models to estimate the dynamic effects of average annual temperature and precipitation on economic growth over recent decades. Kahn et al. (2021) use country-level panel data, while Mohaddes et al. (2022) use data on U.S. states with a relatively small number of lags. In addition to a county-level analysis and a focus on different outcome variables, our work complements this literature by combining longer time-series data on weather with a PDL model, which allows us to capture standard measures of climate change more closely.

Moreover, while prior studies have sought to estimate the effects of weather or climate on *aggregate* economic activity, our focus is on the *spatial distribution* of economic activity. As such, the previous literature generally utilized geographic variation not because of an inherent interest in the effect of weather/climate on the spatial distribution of economic activity but rather to increase statistical power and examine heterogeneous effects.[10]

[9] In addition, their empirical estimates are for shorter horizons – up to 10 years – than the 30-year horizons we focus on in this paper.

[10] Exceptions include the recent spatial equilibrium studies of Cruz & Rossi-Hansberg (2021), Rudik et al. (2022),

Our focus, by contrast, is precisely on identifying the longer-run effects of climate changes on the spatial distribution of economic activity. Indeed, by including time fixed effects in our model, we "sweep out" any aggregate effects of climate changes, thus isolating local relative effects. For example, our historical panel model estimates identify how much local population growth changes – relative to the average county – over time in response to an increase in the number of very hot days – relative to the average county. Combining this estimated model with projected future localized climate changes yields a projection of how population and other economic outcomes will shift, or reallocate, across counties. Extrapolating from these local relative effects to aggregate national or global effects would require alternative and much stronger identifying assumptions.[11]

3 Empirical Methodology

In this section, we describe our empirical methodology. In subsequent sections, we discuss the data, present the historical results, and then estimate projected effects of climate change on the geography of economic activity over the next three decades.

3.1 Panel Distributed Lag Model

Our baseline empirical model is a panel polynomial distributed lag (PDL) model, which is a nested/restricted version of the standard panel distributed lag (DL) model. Hence, to understand the features of the panel PDL model, it is helpful to consider first the panel DL model. That model, relating local outcome growth to current and past weather, is as follows:

$$\Delta y_{it} = \sum_{\ell=0}^{L} \beta_\ell w_{i,t-\ell} + \alpha_i + \alpha_t + \varepsilon_{it} \tag{1}$$

where y_{it} represents the log of some economic outcome (such as employment, population, wages, or house prices) in county i and year t . Hence, Δy_{it} measures the growth rate of the outcome in year t . $w_{i,t-\ell}$ is a vector of local weather variables in year $t-\ell$. In our empirical analysis, we set $L = 29$ such that the model includes 30 years of weather data.

and Bilal & Rossi-Hansberg (2023) and the small set of studies examining internal migration responses to specific shocks induced by climate change. For instance, Feng et al. (2012) examined the relationship between climate change-induced reductions in crop yields and out-migration in rural U.S. counties. Other studies, such as Bohra-Mishra et al. (2014), Marchiori et al. (2012), and Gray & Mueller (2012), have focused on internal migration within developing countries, finding mixed results. As noted in Carleton & Hsiang (2016), "the wide-ranging climatic effects on migration are not well understood and remain an area of active investigation."

[11]Estimates of climate changes' effects on the spatial distribution of economic activity could be augmented with estimates of aggregate effects to obtain absolute, rather than relative, local economic effects. Absolute local effects could then be incorporated into the so-called damage functions used in Integrated Assessment Models (IAMs), which seek to quantify the full economic consequences of climate changes. Auffhammer (2018), Carleton & Greenstone (2021) and Tol (2020) argue strongly for the need for updated research on damage functions to better inform IAMs and policy parameters that rely on them, such as the U.S. government's "social cost of carbon."

As discussed in Dell et al. (2012), this specification allows weather to affect both the level and growth of y. β_L represents the longer-run *growth* effect of a weather shock at time 0. The longer-run *level* effect is given by the sum of the current and lagged coefficients on each weather variable out to L:

$$\Omega^L \equiv \sum_{\ell=0}^{L} \beta_\ell. \tag{2}$$

More generally, $\Omega^h \equiv \sum_{\ell=0}^{h} \beta_\ell$ represents the impulse response function (IRF) of y with respect to a weather shock, dw, at time 0 (Baek & Lee (2021)).

Equation (1) generalizes empirical models previously used to study the economic effects of weather and/or climate change. As discussed above, many prior studies estimated static or short-run autoregressive models, relying on the envelope theorem to infer climate change effects from the estimated contemporaneous weather effects. Other recent studies, most notably Burke & Emerick (2016) and Dell et al. (2012), used a long-difference approach. For example, Burke & Emerick (2016) regressed the 20-year change in a local economic outcome on the 20-year changes in local weather variables using county panel data. As demonstrated in Lemoine (2021), long-differencing is an alternative data transformation to mean-differencing (the standard fixed effects estimator) or first-differencing for removing fixed effects, but it still relies on the same underlying variation in transient weather. In other words, it is an alternative estimator of the purely static model and thus will not capture delayed or longer-run weather effects.

The impulse response function captures both short- and longer-run effects of weather on economic outcomes. Longer-run effects have been referred to as "ex-post adaptation" effects (Lemoine (2021)) because they may reflect delayed adaptation to weather changes that already have occurred. In addition, given intertemporal linkages due to capital or other resource stocks, the behavior of forward-looking agents will depend not only on current and past weather, but also on expectations of future weather. In particular, agents may make adaptive investments today in anticipation of future climate changes, what Lemoine (2021) calls "ex-ante adaptation."

Our empirical model accounts not just for ex-post adaptation, but also for ex-ante adaptation to the extent that it is driven by past weather observations, as is likely the case. In particular, suppose that our outcomes of interest depend on both past weather, due to ex-post adaptation, and expectations of future weather, due to ex-ante adaptation:

$$\Delta y_{it} = \sum_{\ell=0}^{L} \beta_\ell w_{i,t-\ell} + \sum_{h=1}^{k} \delta_h w_{i,t}^{e,t+h} + \alpha_i + \alpha_t + \varepsilon_{it}. \tag{3}$$

As we show formally in Appendix A, if agents have standard adaptive expectations, the expectations terms in equation 3 become linear functions of past weather and the equation collapses to the standard panel DL model:

$$\Delta y_{it} = \sum_{\ell=0}^{L} \tilde{\beta_{i,\ell}} w_{i,t-\ell} + \tilde{\alpha_i} + \alpha_t + \varepsilon_{it}. \tag{4}$$

Though the coefficients now have a different interpretation, this equation contains exactly the same regressors as in equation (1), which reflects two important implications of adaptive expectations. First, any time-invariant component of local expectations will already be captured by county fixed effects ($\tilde{\alpha_i}$). Second, our baseline specification with its inclusion of past weather observations already captures the effects of adaptive expectations to the extent that the weights/coefficients on past weather are homogeneous across counties. Indeed, if agents form expectations in the same way across different counties, the coefficients on $w_{i,t-\ell}$ will fully capture the effects of adaptive expectations. To the extent that agents' expectations processes are heterogeneous, one can allow these coefficients to vary and model that heterogeneity explicitly. For example, in an extension of our baseline results when we allow the impacts of past weather to vary depending on counties' mean climate, the estimated heterogeneous impacts will capture any heterogeneity stemming from counties' expectations processes varying with climate.[12]

Of course, agents may form expectations of future weather using non-adaptive expectations. However, these expectations would need to differ substantially from those implied by adaptive expectations for our baseline specification to be misspecified in an economically meaningful way. Suppose, for instance, that agents ignore weather trends to date and only look to expert projections such as those portrayed in Figures 1 and 2 to forecast future weather. The fact that such projections, at least out to 2050, are highly correlated with recent historical trends across counties implies that the baseline DL model will still largely capture the role of expectations.

3.1.1 Polynomial distributed lag (PDL) model

We impose a polynomial structure on the distributed lag model in equation (1). Specifically, for our preferred specification, we impose a second-order polynomial structure on the coefficients on the weather lags, while freely estimating the coefficients on contemporaneous weather. The estimating equation becomes:

[12]A closely related process of expectations formation is least squares learning (LSL). Under LSL, the parameters in equation (A) would be allowed to vary over time. For instance, if new weather trends emerge over time due to climate changes, agents may increase the weights on more recent weather observations. Similar to allowing for heterogeneity in weights due to county characteristics, one can also allow for LSL expectations by allowing the β_ℓ's in the DL specification to vary over time. Indeed, we do exactly this in Section 5.6 by interacting current and lagged weather with a linear time trend. We find little if any evidence for time-varying marginal weather effects.

$$
\begin{aligned}
\Delta y_{it} &= \beta_0 w_{i,t} + \sum_{p=0}^{2}\sum_{\ell=1}^{L} \phi_p \ell^p w_{i,t-\ell} + \alpha_i + \alpha_t + \varepsilon_{it} \\
&= \beta_0 w_{i,t} + \tilde{\phi}_0 \bar{w}_{i,t} + \phi_1 \sum_{\ell=1}^{L} \ell w_{i,t-\ell} + \phi_2 \sum_{\ell=1}^{L} \ell^2 w_{i,t-\ell} + \alpha_i + \alpha_t + \varepsilon_{it},
\end{aligned} \tag{5}
$$

where $\tilde{\phi}_0 = L\phi_0$.[13] The implied IRF coefficients characterizing the response of the *level* (in logs) of the outcome variable, y, to a weather shock becomes:

$$
\Omega^h = \beta_0 + \tilde{\phi}_0 + \phi_1 \sum_{\ell=1}^{L} \ell + \phi_2 \sum_{\ell=1}^{L} \ell^2. \tag{6}
$$

Note that, because equation (5) models the response of the change in log outcomes to weather as a second-order polynomial, the resulting IRF for the log level, Ω^h, is a third-order polynomial.

This polynomial distribution lag (PDL) specification provides two advantages relative to the unrestricted model. First, the unrestricted model entails estimating a large number of parameters, potentially leading to imprecise estimates of the IRF coefficients. Imposing a polynomial structure allows for increased efficiency.

Second, and more importantly, the PDL model, given a sufficiently long lag length, provides a direct link from standard measures of climate change to the economic outcomes of interest. For each weather variable, the regressor in the first term (when $p = 0$) of the PDL, $\bar{w}_{i,t}$, is the county's (unweighted) average level of that weather variable over the prior 29 years – in other words, a 29-year trailing average. This is approximately equal to the standard measure of a climate "normal" used by climatologists, which is a 30-year average. The regressor in the second term (when $p = 1$), $\sum_{\ell=1}^{L} \ell w_{i,t-\ell}$, is a weighted average of the weather variables over the prior 29 years, where the weights increase linearly with each lag. Hence, this term (times -1) measures the county's linear trend in that weather variable over the prior 29 years. The third term is also a weighted average, but weighting by the square of each lag. Hence, the term captures whether the county's trend in the weather variable has accelerated or decelerated over the prior 29 years.

Thus, by combining our long time-series of local weather with the PDL model, our impulse responses directly capture the impact of local climate changes on our economic variables of interest through changes in mean weather, its trend, and nonlinearity in this trend.

[13] This PDL empirical model is conceptually similar to the approach taken by Bento et al. (2017) in their study of the impact of local climate changes on air quality, which involved regressing local ozone levels on contemporaneous temperature and a 30-year trailing average of past temperatures. The latter term is equivalent to the first ($p = 0$) of the three terms in our second-order polynomial.

3.2 Econometric Concerns

The properties of the DL model and its associated IRFs have been studied recently by Baek & Lee (2021) and Plagborg-Møller & Wolf (2021), who demonstrate that the DL model yields consistent estimates of the true IRF provided that the model includes a sufficient number of lags relative to the horizon of interest. As a result, our long lag structure should yield consistent estimates.

Nonetheless, there are at least two issues that arise with the long-lagged panel DL model, equation (1). First, one *a priori* concern could be that temperature (and possibly precipitation) is trending over time and this trend could introduce nonstationarity in the residuals. For this reason, in their study of the longer-run effect of weather at the U.S. state level, Mohaddes et al. (2022), whose model does not include time fixed effects (or time trends), detrend their weather variables by subtracting a 30-year moving average. In our case, this is unnecessary because the time fixed effects absorb any aggregate weather trends. In addition, our dependent variables are log changes and hence should generally be I(0).

The second issue relates to inference. The error term, ε_{it}, in the DL/PDL models above is potentially serially correlated and likely to be spatially correlated due to the natural spatial correlation of weather. We therefore cluster standard errors by county to account for serial correlation, and by state-year to allow for cross-county correlation within states.

A separate, more general concern with cross-sectional or panel regressions estimating the impact of local shocks on population changes has to do with the role of shocks in alternative locations. Central to both individual location choice and spatial equilibrium models is the notion that individuals choose where to live based on comparisons across locations (as well as migration costs) and so what matters is relative, not absolute, shocks to locations' qualities. Borusyak et al. (2022), following on the spatial lag literature, show that omitting the shocks of alternative locations can cause estimated effects of local shocks on population change to be biased toward zero. They propose a methodology that exploits pre-shock migration patterns to account for shocks in alternative locations. In our setting, given climate changes have been occurring for several decades already, it is infeasible to identify pre-shock migration patterns. However, we address this concern is two ways. First, we show that our results are robust to including region-by-year fixed effects, which will control for weather shocks in a county's region, thus accounting for the possibility that other counties within the region are more relevant alternatives than counties outside of the region. Second, because other counties within a commuting zone are likely to be more relevant alternatives than are counties outside of the commuting zone, we repeat our analysis at the commuting-zone level. We obtain similar results.

4 Data & Stylized Facts

4.1 Economic Outcomes

We use historical county panel data on population, employment, and wages over the past 50 years. Annual county population estimates from 1969 to 2020 were obtained from the Census Bureau. For an extension, we also use data on county population by age from 1970 to 2020 from the National Cancer Institute's SEER program (`https://seer.cancer.gov/popdata/download.html`). From those data we construct population for working-age (20 to 64) and retiree (65+) categories. Annual employment for total industry and for major sectors from 1974 to 2019 were obtained from the Census Bureau, based on the County Business Patterns data, and from Eckert et al. (2021) (`http://www.fpeckert.me/cbp/`). Data on annual nominal wage and salary income by county from 1969 to 2020 were obtained from the Bureau of Economic Analysis (BEA) Regional Economic Accounts database (`https://apps.bea.gov/regional/downloadzip.cfm`). We measure real wages as annual nominal wage and salary income, deflated by the Bureau of Labor Statistics (BLS) consumer price index, divided by annual total employment.

For annual house prices by county, we used the Federal Housing Finance Agency (FHFA) home price index, which is constructed from same-property repeat sales transactions. The data cover 1976 to 2020.[14] One disadvantage of the house price data is that they are unavailable for less populous counties, so data are available for only roughly 2,400 of the nation's 3,140 counties.

4.2 Historical Weather

We make use of a novel new data set, the NOAA Climate Divisional Database (NClimDiv). Produced by NOAA's National Center for Environmental Information (NCEI), NClimDiv contains long historical weather data at various levels of spatial aggregation. Spatial aggregates are calculated from area averages of 5 km gridded estimates based on daily readings from the Global Historical Climatological Network (GHCN) of weather stations (Vose et al. (2014)). As of November 2018, NClimDiv has provided county-level area averages of daily temperatures – maximum, minimum, and average – and precipitation from January 1, 1951 to present.

From these daily records, we construct the following six yearly weather variables from 1951 to 2020:

1. Number of days in the year in which the daily average temperature was below 20°F (≈ -6.7°C)
2. Number of days in the year in which the daily average temperature was between 20 and 50°F (-6.7-10°C)

[14] For a small number of counties, the FHFA index is missing for some counties while an analogous index from CoreLogic is available. We use the CoreLogic index in those cases.

3. Number of days in the year in which the daily average temperature was between 70 and 80°F (21.1-26.7°C)

4. Number of days in the year in which the daily average temperature was above 80°F (26.7°C)

5. Average daily precipitation (mm)

6. Number of days with extreme precipitation (defined as daily precipitation above its 99th percentile across all county-day observations from 1951-2020)

The use of such temperature bins, rather than annual averages, allows for potentially nonlinear effects and follows several prior studies such as Deschênes & Greenstone (2011), Burke et al. (2015), and Deryugina & Hsiang (2017). We use daily average temperatures to form our temperature bin variables. Note that the daily average is generally around 10 °F below the daily maximum. Hence, days with a daily average temperature above 80°F (26.7°C) are similar to days with a daily maximum temperature above 90°F (32.2°C).

To give a sense of how these bins relate to the full temperature distribution, panel A of Appendix Figure A1 shows the percentage of days from January 1, 1951 to December 31, 2020 for which the daily average temperature fell within each 5-degree (Fahrenheit) bin, averaged over all U.S. counties. Vertical red lines are shown at 20, 50, 70 and 80 degrees, which are the cut-points we use to construct the temperature frequency bins. The cut-points of 20 and 80 are close to the 5th and 95th percentiles of the distribution. The cut-point of 50 is around the 40th percentile, while the cut-point of 70 is around the 75th percentile.

4.3 Weather Projections

In Section 6, we provide results using projections of county-level weather constructed in Hsiang et al. (2017) and Rasmussen et al. (2016). These are projections of the distribution of daily average temperature and daily precipitation across days of the year, for each year from 1981 to 2100 and for every county in the contiguous United States. These county-level series are spatially downscaled projections based on alternative global greenhouse gas concentration scenarios, known as Representative Concentration Pathways (RCPs), from the U.N. Intergovernmental Panel on Climate Change (IPCC) Fifth Assessment Report (AR5). Our baseline results use the county weather projections corresponding to the RCP 4.5 scenario. This scenario is based on a continuation of current global climate policies and projects a global temperature increase of 2.5 to 3.0°F (1.4 to 1.7°C) by 2100. We also produce results using the RCP 8.5 scenario, which is frequently described as a worse-case scenario. While the RCP 8.5 weather projections exhibit larger trends in temperature rise for the United States as a whole, the cross-county correlation between RCP 4.5 and RCP 8.5 is close to one. Thus, the county-level projections of economic outcomes from the RCP 4.5 and RCP 8.5 scenarios are extremely similar except that the latter have a larger range.

Figures 1 and 2 show the historical and the projected yearly trends in each of the weather variables used in our empirical analysis. These maps reveal a number of clear patterns. First, the southern regions generally have seen an increase in the number of extreme heat days – defined as days with an average temperature above 80°F (26.7°C) over the past 70 years, while the Midwest has seen a slight reduction (see panel (a) of Figure 1). Going forward, nearly all counties are projected to see more extreme heat days, though the largest increases are expected in the southeastern quarter of the country (see panel (b)). Second, northern and western parts of the country have seen more moderately hot days – with an average temperature between 70 and 80°F (21.1 and 26.7°C) – over past decades (see panel (c)), and this trend is expected to continue over at least the next three decades (see panel (d)). By contrast, southern regions have seen and are expected to continue seeing fewer moderately hot days, which are being increasingly replaced by extremely hot days. Third, the northern Midwest and the Mountain West experienced an increase in the number of moderately cold days – with an average temperature between 20 and 50°F (−6.7 and 10°C) – since 1950, while the rest of the country saw a decline (see panel (e)). Looking ahead, everywhere except the upper Midwest is projected to see fewer moderately cold days (see panel (f)). Fourth, the number of very cold days – with an average temperature below 20°F (−6.7°C) – has declined, and is projected to continue to decline, in the upper Midwest, Northeast, and Mountain West regions. In other regions, both the historical trend and the projected trend for the number of very cold days is close to flat because such days are rare in those regions. Lastly, Figure 2 shows that the trends in both overall precipitation and the number of extreme precipitation days vary substantially across the country. A band running from east Texas to Maine has experienced a substantial increase in average precipitation (see panel (a)). That trend is projected to continue, though many other regions (Southeast, Southwest, and southern California) are projected to become drier. Historical trends and projections for extreme precipitation are more spatially heterogeneous (see panels (c) and (d)).

5 Historical Results

5.1 Simple Graphical Evidence

Before estimating the full IRFs with respect to weather shocks using the distributed lag model laid out in Section 3.1.1, we first provide some simple graphical evidence that illustrates the key correlations determining the longer-run level effects (Ω^L in equation 6). The longer-run effect for any given weather type estimated from the PDL model given by equation (5) will depend, after differencing out time and county fixed effects, on the partial correlations between county growth (Δy_{it}) and each of three variables. Recall that the first term of the second-order polynomial in equation (6) represents a county's mean level of the weather variable over the prior 29 years. The second term (times -1) is the county's linear trend in that weather variable over the prior 29 years, and the third term (times -1) is the quadratic component, capturing whether the trend is accelerating or decelerating. It turns out that the estimated IRFs are broadly similar whether we use a linear or a quadratic PDL specification, so here we focus on the first two terms.

Figure 3 shows a simple scatter plot for each of these two terms, first for the number of extreme heat days (left panels) and then for the number of extreme cold days (right panels). For each county, the scatter plot compares the 1980-2020 change in that term with the 1980-2020 change in population growth.[15] The purpose of taking the change in each variable is to remove county fixed effects, as in the PDL regression model. Each dot in the plots represents a single county. The red line in each panel is a linear OLS regression fit line.

The first scatter plot (panel (a)) reveals a clear negative relationship across counties between the change in population growth and the change in the mean number of extreme heat days over the prior 29 years. That is, while the vast majority of counties saw population growth slow over the past four decades, those whose growth slowed the most have been those where the average number of extreme heat days increased the most. In addition, as shown in panel (b), counties with more positive trends in the number of extreme heat days also tended to see greater slowing in population growth. Taken together, these plots show that population growth in the United States over the past 40 years has slowed more in places experiencing more extreme heat and places where the trend in extreme heat has increased the most. Panels (c) and (d) reveal analogous patterns for extreme cold: population growth has generally slowed less in counties where the number of extreme cold days fell more and whose trend in extreme cold days is more negative. The formal regression analyses below confirm these patterns for extreme heat and population and will reveal similar patterns for employment, wages, and house prices.[16] We will also uncover the relationships between these economic outcomes and other weather variables.

5.2 Baseline Regression Results

Figure 4 shows the estimated impulse response functions for population with respect to each of the six weather variables. The IRFs plot Ω^h in equation (6) for $h = 0$ to 29, for each of the weather variables, based on estimating the baseline PDL specification (equation (5)). We first find that weather has no contemporaneous effect on population. In a sense, this result is not surprising. Local year-to-year population changes are primarily driven by migration (as opposed to differences in births and deaths), and standard economic models of migration decisions emphasize that the net benefit of moving must be fairly large to offset moving costs. Hence, transitory fluctuations in weather should not induce migration.

However, we find that several types of weather have statistically significant effects arising rel-

[15] To reduce noise stemming from idiosyncratic transitory shocks to county population growth at these endpoints, we measure population growth in 1980 and 2020 using a 10-year trailing average and winsorize at the 1st and the 99th percentiles.

[16] Analogous scatter plots for employment, wages, and house prices are provided in Appendix Figures A2 – A4.

atively rapidly and increasing over the medium to longer run. In particular, the number of very hot (average temperature between 70° and 80°F (21.1-26.7° C)) and extremely hot (above 80°F (26.7°C)) days both have a negative and highly statistically significant effect on county population over these horizons. For example, the Ω^{29} IRF coefficient of -0.05 implies that an increase of one extremely hot day in a single year, and one less day in the omitted category of 50° to 70°F (10° – 21.1°C), reduces local population 30 years hence by 0.05 percent. While this effect from a single year increase is small, the implied effect from a long sequence of yearly increases can be substantial. For instance, if the number of extreme heat days per year in a given county were to permanently increase by 10, after 30 years population would be reduced by $300 \times (-0.054) = 16.2$ percent. We also find large longer-run negative effects from extreme cold days. We find no significant longer-run effects for either precipitation variable, though we do see a medium-run decline in population in response to extreme precipitation.

Panel (a) of Figure 5 visually summarizes these key moments from the estimated population IRFs. Specifically, it plots the estimated contemporaneous effects (Ω^0, shown in red) and the longer-run effects ($\Omega^2$9, shown in blue) for each of the six weather variables. For instance, the blue dot in the "70-80" column, with a y-axis value of -0.054, corresponds to the end-point (year 29) of the IRF shown in panel (a) of Figure 4, whereas the red dot near the zero line in that column corresponds to the initial (year 0) point of that IRF. Panels (b)-(d) plot the same key moments from the estimated IRFs for employment, house prices, and wages, respectively.[17]

Overall, the results for employment are similar to those for population. Short-run effects are generally small and not statistically significant, while we find large negative longer-run effects in many cases. For instance, the IRF coefficient at the 30-year horizon for extreme heat is -0.07, which implies that an extra day of extreme heat (relative to the omitted category) in a year reduces local employment 30 years ahead by 0.07 percent. We find that cold and extreme cold days also have longer-run negative effects on employment, whereas the precipitation variables have no significant longer-run effects.[18]

We next consider the effects of weather on annual wages. Hot days and extreme heat days have small negative effects in the short run and larger negative effects in the longer run. The IRF coefficient at the 30-year horizon is roughly -0.04 for hot days and -0.05 for extreme heat days. No significant wage effects are found for cold, extreme cold, and extreme precipitation. However, we find that increases in average annual precipitation have a negative effect on wages over the longer run.

[17]The numbers underlying this figure and the IRFs for employment, house prices, and wages are provided in Online Appendix Figures A5-A7 and Table A1.

[18]The negative longer-run effect of extreme temperatures on employment can be analyzed in greater detail by looking at sectoral employment. Online Appendix Figure A8 shows the results of estimating our baseline PDL model separately for employment in each major sector. The results point to negative and significant longer-run effects of hot days and/or extreme heat days in weather-sensitive sectors such as Retail, Transportation, and Wholesale. We also find large longer-run negative effects of cold and/or extreme cold days on employment in several sectors, especially Agriculture, Construction, Manufacturing, Mining, and Retail.

Turning to house prices, we find that they decline over the longer run in response to increases in the number of hot days and extremely hot days, though the latter is statistically insignificant. As for wages, precipitation also has a negative longer-run effect on house prices, statistically significant at the 90 percent level.

In sum, these results indicate that both population and employment are affected by temperature over the longer run in an inverse-U shaped pattern, with both cold and hot days having negative effects. For house prices and wages, only hot days have negative longer-run effects. Average annual precipitation also has negative effects on house prices and wages over the longer run, while having no significant effect on population or employment.

To shed light on the mechanisms explaining how local climate changes affect these outcomes, we present results in subsection 5.5 below for amenities and productivity, the key structural factors determining population, employment, wages, and house prices according to our spatial equilibrium model in Appendix B. First, however, in the next two subsections we assess the sensitivity the results for these observed outcomes to alternative specifications and to the level of aggregation.

5.3 Robustness and Alternative Specifications

In this subsection, we evaluate the sensitivity of the baseline PDL model's results to alternative specifications, sample restrictions, and removing population weighting.

We focus on the sensitivity of our key empirical moments of interest: the longer-run level effect ($\hat{\Omega}^{29}$) for each outcome with respect to the different weather variables. Results for a range of alternative specifications are provided in Figure 6. [19] The far-left series in each plot re-displays the estimated longer-run weather effects from the baseline PDL results, the same series shown (in blue) in Figure 5. The next series to the right report the results when we include a lagged dependent variable in the model. In our baseline model, we omit a lagged dependent variable because the model's residual term should be approximately stationary for two reasons. First, time fixed effects absorb any aggregate trends. Second, our dependent variables are log changes, so I(0). With a lagged dependent variable, the longer-run effects are calculated as the sum of the coefficients on the contemporaneous and lagged weather variables divided by the coefficient on the lagged dependent variable. The estimated effects in this case are very similar to those from the baseline DL model.

The third series in the panels of Figure 6 shows the longer-run weather effects estimated using the unrestricted distributed lag model (equation 2) – i.e., the model without imposing a polynomial structure on the coefficients of the 30 weather lags. The estimated effects are very similar.[20]

We next explore the sensitivity of the results to the number of weather lags included. The fourth series in Figure 6 repeats the estimation of the unrestricted DL model but with 9 rather than 29 lags in the baseline model (that is, 10 years of weather including the contemporaneous value). In

[19] The numbers underlying this figure, as well as the estimated contemporaneous effects, are provided in Online Appendix Tables A2 – A5.

[20] The full IRFs for this unrestricted model are provided in Online Appendix Figures A9 – A12.

general, the estimated longer-run effects are qualitatively similar to our baseline results, though closer to zero. In particular, for employment and house prices, the estimated effects of hot and extremely hot days become statistically insignificant.

The remaining series highlight the concerns with inferring longer-run effects of weather from the estimated short-run effects. For instance, we shorten the lag length further, to just three years, in the fifth series and down to just one year in the sixth series. The seventh and final series shows the results when we drop lags of weather altogether. We see that estimated longer-run effects generally become closer to zero and less statistically significant (despite smaller standard errors) as one shortens the number of lags. As a result, empirical models with no lags or a limited number of lags will only partially capture the longer-run effects of climate change.

In Figure 7, we consider the sensitivity of the results to several other alternative empirical models, focusing on our key empirical moment of interest, the longer-run level effect ($\hat{\Omega}^{29}$). The far-left series in each plot re-displays the baseline PDL results from Figure 5. The next series to the right tests whether the results are robust to dropping the large Sunbelt cities of Houston, Dallas, Phoenix, Miami-Fort Lauderdale, and Tampa-St.Petersburg. Specifically, we exclude the 31 counties comprising these five commuting zones. These cities in Texas, Arizona, and Florida have seen some of the largest increases in annual extreme heat days over the past 70 years in the country (Figure 1) while also seeing rapid population growth, though that growth slowed to some extent over time. While county fixed effects will absorb each county's mean population growth (and mean growth in employment, wages, and house prices in their regressions), it is possible that the slowing in growth over time was an inevitable result of congestion effects as these cities became heavily populated, and not driven by climate changes. However, one can see in Figure 7 that we obtain very similar results as the baseline even after dropping these cities.[21]

We also examine whether the baseline results are unduly driven by coastal counties which *a priori* could be more sensitive to climate changes either because extreme precipitation in coastal areas is more likely to be associated with costly hurricanes or because hot days are less of a disamenity in areas with beaches. To assess this, we re-estimate the baseline PDL model excluding coastal counties. We find the results are little changed, indicating the effects of climate changes are similar in coastal and non-coastal areas.

The next series in Figure 7 assesses how important population weighting is for our main results. It shows the estimated longer-run effects from estimating the baseline model using unweighted OLS. As one would expect if measurement error was present in the outcomes and/or the weather variables are inversely related to population, the unweighted regressions tend to produce larger confidence intervals. Nonetheless, the point estimates from the unweighted regressions generally are quite similar to the baseline model with population weighting.

Lastly, we examine the possibility that unobserved local trends, correlated with local climate

[21] We also obtain very similar results to the baseline if we drop all counties in the key Sunbelt states of Florida, Texas, and Arizona.

changes, could be biasing our estimates of longer-run weather effects. We examine this in three ways. First, we add region-specific linear time trends to the baseline model. The results are shown in the next series to the right in Figure 7. Note that the county fixed effects in the population growth and employment growth regressions already capture the longer-run migration trends in the United States over the past several decades from the North to the South and West, stemming from factors such as the diffusion of air conditioning in the South (Barreca et al. (2016)), right-to-work laws in the South (Holmes (1998)), the de-industrialization of the North, and the general "moving-to-nice-weather" trends (Rappaport (2007)). Region-specific linear time trends in these growth regressions will absorb any deceleration over time in these region-to-region movements. We find the longer-run weather effects are generally robust to accounting for these trends.

Second, we allow the time fixed effects in the baseline model to vary by region. In this case, identification stems from cross-county variation in changes over time in weather and growth in the outcome variable *within a region*. Region-specific time fixed effects will absorb not only the aforementioned secular trends in migration between regions but also higher frequency shocks to entire regions. The results are again generally similar to the baseline results. One exception is the results for precipitation. This specification yields a negative and significant effect of precipitation on employment but no effect on wages, where as the baseline specification yields a negative and significant effect on wages but no effect on employment. Thus, while we can be fairly confident that precipitation reduces local wage bills in the longer-run, it is not entirely clear whether the result comes primarily from employment or wages.

Third, we consider whether "pre-trends" in weather – omitted in our baseline specification – could be biasing our longer-run weather effect estimates. In our setting, the concept of "pre-trends" is complicated because, as discussed earlier, part of the longer-run economic effects of past weather may be through ex-ante adaptation. For example, households may choose to move in response to past adverse weather shocks because those past shocks alter households expectations of climate – i.e., the probability distribution of weather shocks – going forward. However, it is also possible that agents form expectations based on other information, either in addition to or instead of past weather realizations. Because our baseline specification omits this information, which could be correlated with past weather, this could lead to an omitted variable bias. To test this, we add 10 leads of the weather variables to our baseline PDL specification (equation 5). The results are shown in Appendix Figure A13. For comparison, we also re-estimated the baseline PDL specification for this sample, which is 10 years shorter because of the addition of the 10 leads. We find that including future weather realizations has virtually no effect on the estimated longer-run effects of past weather. This suggests that, to the extent that our results are driven by ex-ante adaptation, agents' expectations are well-approximated by adaptive expectations.

5.4 Commuting Zone Results

A potential concern with using county-level variation to study the effects of place-based climate changes on our variables of interest is that people do not need to live in the same county in which they work. Yet, at least prior to the recent surge in remote work, people generally have lived and worked in the same local labor market or commuting zone. If people are able to work in a county that has an adverse climate but high labor demand (e.g., firms may locate in poor climate areas because of cheap land and/or natural resources) while living in a nearby county that has a better climate, differences between the population response to climate changes and the employment response, and differences between the house price response and wage response, could be misleading. In addition, people and firms considering moving may think more about the climate of a local labor market than a narrower area such as a county, because a local labor market is more informative about future employment and market opportunities. If so, climate changes in the local labor market will be more relevant than those at the county level. In particular, because our baseline model omits weather in other counties within the same local labor market, which is correlated with weather in the focal county, if adverse climate changes in those nearby counties directly affects our outcome variables, our estimated effects will be biased. The bias would be away from zero if adverse climate changes in nearby counties just exacerbate the negative impacts of own county weather on amenities and productivity. The bias could be toward zero if people are relatively immobile across commuting zones but mobile within zones. In that case, negative climate changes in a county's neighbors will at least partially offset the effects of that county's own negative climate changes.

We examine these issues by aggregating our data to the commuting zone (CZ) level and then re-estimating our baseline PDL model. Our CZ definitions come from the Census Bureau and correspond to 1990 commuting zones. We aggregate population and employment simply by summing across counties within the CZ. For the house price index and each of the weather variables, we take a population-weighted average of the variable across counties within the CZ. For wages, we sum county real wage and salary income within the CZ and divide by total CZ employment. Using these CZ-level data, we estimate equation 5 with i now denoting CZs and α_i representing CZ fixed effects. Standard errors are based on clustering by CZ (to account for serial correlation) and year (to account for spatial correlation across CZs).

The CZ-level estimates of the longer-run weather effects ($\hat{\Omega}^{29}$) are shown in Figure 8. The figure also re-displays the county-level results from Figure 5 for comparison. The CZ-level results are generally quite similar, both qualitatively and quantitatively, to the county-level results, though they are less precisely estimated due to the smaller number of observations. In particular, extremely cold days, hot days, and extremely hot days reduce population over the longer run at the CZ level by a similar magnitude as we found for the county level. Hot days are also still found to lower house prices, but the effect at the CZ level is no longer statistically significant. For wages, the CZ-level results are broadly similar to the county level results, showing declines in wages for hot days, extremely hot days, and precipitation. We also continue to find a negative longer-run effect on employment from cold and extremely cold days. However, the employment effects of hot and extremely hot days are no longer statistically significant. Overall, the similarity between county- and CZ-level results suggests that any bias stemming from cross-county spillovers within local labor markets is likely to be minimal.

5.5 Implied Effects of Climate Changes on Amenities and Productivity

To examine the theoretical mechanisms by which local climate changes affect the spatial distribution of population, employment, wages, and house prices, we develop a simple spatial equilibrium model, which we summarize below. The full model is presented in Appendix B. In the spirit of Rosen (1979) and Roback (1982), our spatial equilibrium model points to local amenities and productivity (A_l and z_l, for a given location l) as the key structural factors determining these spatial allocations.

As the appendix describes, our framework builds on the model of Hsieh & Moretti (2019), but splitting households into two types: workers and non-workers, which, for simplicity, we refer to as "retirees." This modeling approach is useful in interpreting the different empirical responses of employment and population to weather variables. Absent this distinction, there would be no difference between employment and population when the population in each location is assumed to be fully employed, the standard assumption in most models in the literature.

In addition to deciding in which regions to live, households choose their consumption of traded and nontraded goods (e.g., housing). Workers receive wage income derived from inelastically supplying one unit of labor to firms in their location. Retirees receive a fixed income from the federal government ("retirement benefits"). For simplicity, workers and retirees are hand-to-mouth agents and therefore fully consume their income each period. In each location, perfectly competitive firms produce a costlessly traded good subject to local productivity shocks. Similarly, firms in the housing sector produce housing services using a combination of traded goods and land. Both types of households choose where to locate based on their utility. By impacting local productivity and amenities, climate changes affect local economies through household consumption, production, and location decisions (see, also, Desmet & Rossi-Hansberg (2015), Desmet et al. (2018), Cruz & Rossi-Hansberg (2021), Nath (2020)).

In this subsection, we use a calibrated version of the model, combined with the data on observed outcomes, to back out these structural factors for every county and year in our historical sample.[22] We then estimate the longer-run effects of climate changes on local amenities and productivity using the same empirical specification – the PDL model – used above (i.e., setting $y_{lt} \equiv log(Y_{lt})$ in equation (5) to $log(A_{lt})$ or $log(z_{lt})$).

In Appendix B, we show that the log values of amenities (A_{lt}) and productivity (Z_{lt}) can be

[22] Given that the model is static, we impose the equilibrium conditions period by period to infer the levels of amenities and productivity at each point in time. See Bilal (2023) and Kleinman et al. (2023) for recent approaches for solving dynamic spatial equilibrium models.

derived from the model's equilibrium conditions as functions of worker population (L^w_{lt}), retiree population (L^r_{lt}), and house prices (p_{lt}). The following expression gives the log values of amenities:

$$log(A_{lt}) = (1/\theta)log(L^r_{lt}) + (1-\alpha)log(p_{lt}) + f^r_t, \tag{7}$$

where θ is a parameter governing the strength of idiosyncratic location preferences, α is the share of housing in households' expenditure, and f^r_t is a latent variable reflecting retirees' benefits and their average indirect utility across all locations. Because f^r_t only varies by time, not by location, it will be absorbed in our regressions by the time fixed effects and need not be observed. This equation makes clear that the longer-run effect of a given weather variable on the amenity value of a location (relative to the rest of the nation) is a weighted sum of the effects on non-worker population and house prices (p_{lt}), with positive weights.

Similarly, the log values of productivity can be expressed as follows:

$$\begin{aligned} log(z_{lt}) &= (1-\phi+1/\theta)log(L^w_{lt}) - (1/\theta)log(L^r_{lt}) + \alpha log(p_{lt}) - f^r_t + f^w_t \\ &= (1-\phi+1/\theta)log(L^w_{lt}) - (1/\theta)log(1-L^w_{lt}) + \alpha log(p_{lt}) - f^r_t + f^w_t, \end{aligned} \tag{8}$$

where ϕ is the labor elasticity in traded good production and f^w_t reflects workers' average indirect utility across all locations. Like f^r_t, f^w_t only varies by time, not by location, and will be absorbed in our regressions by the time fixed effects. From equation (8), we see that the longer-run effect of a given weather variable on local productivity (relative to the rest of the nation) is a weighted sum of the effects on worker population, non-worker population, and house prices. Increases in worker population and house prices or declines in non-worker population are associated with greater productivity. Comparing equation (8) to equation (7), one can see that the key to separately identifying productivity from amenities is the level of worker population relative to non-worker population and house prices.

We calibrate the parameters such that the share of housing in households' expenditures is $\alpha = 0.3$, the labor elasticity in traded good production is $\phi = .7$, and the strength of idiosyncratic location preferences is given by $1/\theta = 0.2$. Since the model abstracts from unemployment fluctuations (based on the assumption that climate changes do not affect steady-state unemployment rates), we measure worker population using employment, which implies the non-worker population is simply total population minus employment.

The estimated marginal effects of each weather variable on our model-implied values of amenities and productivity are shown in Figure 9. To help with interpretation, we also show the estimated marginal effects for the non-worker population. As in Figure 5, we plot both the contemporaneous and longer-run (30-year out) effects. Consistent with the lack of contemporaneous weather effects on population, employment, and house prices in Figure 5, we find no significant contemporaneous effects on either amenities or productivity. By contrast, we find larger and more significant longer-run effects. In particular, increases in heat and extreme heat days and in precipitation reduce both amenity values and productivity (though the effect of precipitation on productivity is not quite statistically significant). Cold days and extreme cold days, on the other hand, reduce productivity (though the effect of extreme cold days is not quite statistically significant) but have virtually zero effect on amenities.

These changes in amenities and productivity help us interpret the results for our observed outcomes. In particular, the negative effects of hots days on population, employment, and house prices in Figure 5 can be attributed to reductions in both amenities and productivity. In addition, notice that cold days have much larger negative effects on employment than they do on non-worker population, which may even increase, and they have no effect on house prices. These relatively large negative effects on employment can be attributed to the negative effects of cold days on productivity. Through the lens of the model, cold days reduce productivity leading to a negative effect on employment. This puts downward pressure on house prices, but that downward pressure is offset by upward pressure from a higher non-worker population, with non-workers attracted by (and offsetting) any declines in house prices combined with unchanged amenities. Lastly, we find that precipitation reduces house prices, while having no effect on population or employment. This can be explained by the finding that precipitation reduces both amenities and productivity, reducing both non-worker and worker populations, which unambiguously lowers house prices. The decline in productivity can also explain the negative effect of precipitation on wages.

5.6 Allowing for Heterogeneity

The true impacts of climate changes on local economies are likely to be heterogeneous, differing depending on various characteristics of the local area. Two important characteristics examined in prior studies are income and typical climate.

To look at the role of local area income, we extend the baseline specification by interacting each weather variable with "high income" and "low income" indicators, measuring whether the county is in the top third (tercile) or bottom third, respectively, in terms of mean income per capita over 1951-2000. These interactions allow us to test whether economic outcomes respond differently to weather shocks in richer counties. The estimated longer-run effects are shown in the top row of Figure 10. We find substantial evidence of heterogeneity in weather effects in terms of county income, especially for population. In particular, we find stark differences in the marginal effects of weather on population over the longer run for high-income versus low-income counties. The effects of hot days, cold days, and precipitation are negative and significant for low-income counties, but positive and significant for high-income counties. The negative effects are generally larger, in absolute value, than the positive effects, consistent with the negative average-county effects found earlier.[23] A likely explanation for this result is that low-income areas are more negatively impacted by adverse weather

[23]This result is reminiscent of the cross-country findings of Dell et al. (2012), which pointed to negative temperature effects for low-income countries but no significant effects for high-income countries.

shocks because they are less able to afford adaptation technologies/capital, such as air conditioning, insulation, levees, and pumps, and associated energy costs. High-income counties, by contrast, are less negatively impacted, or even positively impacted, due to these adaptive investments.

We next investigate whether the marginal effects of weather depend on the historical/typical climate of a local area. Similar to Carleton & Hsiang (2016), Nath (2020), and Carleton et al. (2020), we extend our baseline specification by adding, for each weather variable, an interaction between the variable and an indicator for whether the county's 1951-2020 average of that variable is above the median across all counties. For example, in addition to having the number of days in a county-year with a daily average temperature below 20°F (-6.7°C), we add an interaction between that variable and an indicator for whether the county is among the top half of counties in terms of its average annual number of below 20° days. Counties with high average values for a given weather variable likely are better adapted, or "more accustomed," to that type of weather. These interactions allow us to test whether economic outcomes in such counties respond less, or at least less negatively, to shocks in each type of weather.

The estimated longer-run effects, separated for counties above and below the median for each weather variable, are shown in the middle row of Figure 10. The IRFs for counties more accustomed to that type of weather are shown in red, while counties less accustomed to that type of weather are shown in blue. In general, we find that counties more acclimated to a given type of weather in many cases tend to benefit in terms of population and employment compared with other counties. This could reflect the role of learning/adaptation. As we showed in Appendix A, agents with adaptive expectations will anticipate a given type of weather based on past experience. As a result of historical adaptation to their typical climate, better acclimated regions may be more attractive and productive places to live and work.

Of course, expectations of future climate in a given area likely come not just from observing past weather and trends, but may also be colored by ideological beliefs. To examine this possibility, we make use of the Yale Climate Survey.[24] This survey, conducted annually from 2014-2021, asks households throughout the United States about climate change beliefs. In particular, one question simply asks households, "Is global warming happening?" We use the fraction of respondents within each county answering yes as a crude measure of climate change belief. We assume that this fraction for 2014-21 is roughly proportional to its true 1969-2020 average. That is, while there has probably been an upward trend in that variable nationally, the cross-county distribution likely has been fairly stable. The estimated marginal weather effects in places more accepting of global warming are more likely to reflect changing, forward-looking expectations than are more climate-denying places. Similar to the analyses of county income and historical climate, we interact each weather variable (and its lags) with a high-global-warming-belief dummy variable and a low-global-warming-belief dummy variable, corresponding to counties in the top and bottom terciles of that fraction's distribution.

[24] https://climatecommunication.yale.edu/visualizations-data/ycom-us/

The results are shown in the bottom panel of Figure 10 . Interestingly, the negative longer-run effects of cold days and hot days on population appears to be isolated to counties whose residents are skeptical of global warming. By contrast, cold and hot days are found to have positive effects on population in counties with greater belief in global warming. One possible hypothesis explaining these results is that places anticipating increasing temperatures in the future have made adaptive investments to not only tolerate their local climate changes but indeed to take advantage of them. By contrast, places in denial of global warming are likely not making these investments and hence are seeing their local amenity and/or productivity values deteriorating, leading to relative population declines over time. Similarly, we find positive longer-run employment effects for hot and extremely hot days in counties with greater belief in global warming, though this is not a generalized pattern across all weather variables.

Lastly, we examine whether the longer-run marginal weather effects have changed over time. Forward-looking expectations, such as least-square learning, are one reason climate changes could cause these effects to change over time, as discussed in Section **??**. In addition, the amenity or productivity values of particular types of climate could change over time. To test for time-varying marginal weather effects, we add, for each current and lagged weather variable, an interaction with a linear time trend (i.e., year minus 1980). We then report the implied 30-year effects for each weather variable as of 1980 and 2020. The results, shown in Appendix Figure A14, indicate that there has been little if any change in these longer-run effects over time, consistent with households having approximately adaptive expectations and there being little change in the amenity and productivity values of climate over time.

6 Projections

6.1 Methodology

In this section, we examine how climate changes over the decades ahead may affect the economic geography of the United States? Specifically, we combine the estimated PDL model (with and without heterogeneous effects) with county-level weather projections to forecast changes in population and employment from 2020 to 2050 for every county in the contiguous United States. To isolate the projected change in each outcome due solely to climate changes, we calculate the difference between the projected change under a climate change scenario and the projected change under a no climate change scenario.

To forecast how a given outcome, y_{it}, will change over the next few decades, we first predict annual growth in that outcome for each out-of-sample year from 2021 to 2050 based on the parameter estimates of equation (5) and weather values for a given scenario s.

$$\widehat{\Delta y_{it}^s} = \sum_{\ell=0}^{L} \sum_{p=0}^{2} \hat{\phi}_p \ell^p w_{i,t-\ell}^s + \widehat{\alpha}_i. \tag{9}$$

We then obtain projected longer-run changes in outcomes from 2021 to 2050 ($\widehat{y_{i,2050}^s - y_{i,2020}^s}$) by cumulating the predicted yearly changes ($\widehat{\Delta y_{it}^s}$) over 2021 to 2050.

Finally, we calculate the changes due solely to climate change by taking the difference in $\widehat{y_{i,2050}^s - y_{i,2020}^s}$ under a climate change (CC) scenario and a no climate change (0) scenario:

$$\Delta \widehat{y_{i,2020-50}^{CC,0}} = \left(\widehat{y_{i,2050}^{CC} - y_{i,2020}^{CC}}\right) - \left(\widehat{y_{i,2050}^{0} - y_{i,2020}^{0}}\right) \tag{10}$$

The climate change scenario is based on the county-level weather projections constructed in Hsiang et al. (2017) and Rasmussen et al. (2016) corresponding to the IPCC RCP 4.5 global greenhouse gas scenario (see Section 4 for further description). For each county and each weather variable in our model, we first construct a provisional projected value for each year from 2021 to 2050 based on the projected within-year distributions of daily temperature and precipitation given by Hsiang et al. (2017). We then estimate the county-specific linear trend from 2021 to 2050 for each variable. Our final projections assume each weather variable starts at its observed value in 2020 and then follows this trend until 2050. The no climate change scenario assumes that each weather variable is constant from 2021 to 2050 and equal to its 1991–2020 county-specific mean.

There are three important considerations regarding the interpretation of these projections. First, note that the estimated county fixed effects in equation 9 are the same in both scenarios and hence get differenced out in equation A15. Second, past weather values are the same under both scenarios. Thus, $\Delta \widehat{y_{i,2020-50}^{CC,0}}$ captures the projected change in the outcome variable for each county due solely to projected future climate changes. Third, equation (9) assumes the time fixed effects, α_t, in the historical regression model (equation (1)) are equal to zero in out-of-sample years. The time fixed effects in the historical regression model absorbed past aggregate (i.e., national or global) shocks. Setting future aggregate shocks to zero, in both scenarios, implies that the resulting $\Delta \hat{y}_{it}$ for future years should be interpreted as projections of local growth *relative to the national average*. In order to interpret these projections as projections of the absolute change in population or employment for each county, inclusive of national/global climate change effects as well as other national growth shocks, one would need to add auxiliary projections of national growth under each scenario.

In sum, our estimates provide projections of the change in the spatial distributions of population and employment between 2020 and 2050 due to projected future climate changes.[25]

[25]For employment outcomes, 2019 is the latest year of data, so projections are changes from 2019 to 2050 rather than 2020 to 2050 as is the case with population.

6.2 Results

6.2.1 Geographical Pattern of Reallocation

Our estimates of $\Delta \widehat{y_{i,2020-50}^{CC,0}}$, based on the baseline PDL model, are shown in Figure 11 for each of the economic outcomes. The projected climate changes are predicted to cause a general shifting of population from the Southeast and parts of the Southwest to the North, the Mountain West, and most of the Pacific coastline. These patterns are driven primarily by the projected trends toward relatively more extreme heat days in the Southeast and Southwest. The projected shifts in the spatial distribution of employment show a similar pattern to that of population.[26]

These projected movements in people and jobs would represent a dramatic reversal of the late 20th century pattern of movement from the Northeast and industrial Midwest toward the Sunbelt. One way to see this shift is by examining how the geographical correlation between population growth and climate has changed over time. The top four scatter plots in Figure 12 show the relationship between historical extreme heat climate – measured by the average number of extreme heat days per year over 1951-2050 – and average population growth for each of the past four decades. The bottom two scatter plots show the same relationship using our projections for county population growth (based on RCP 4.5), for 2021–2035 and 2036–2050. The link between extreme heat and population growth was strongly positive in the 1980s, with a slope coefficient 0.01 and a t-statistic above 10. However, that relationship weakened substantially over the subsequent two decades and vanished entirely over 2010-2020. The projections for the decades ahead show a continuation of this pivot, turning modestly negative over 2021-2035 and strongly negative over 2036-2050. The change in this correlation over time (at least historically) could reflect changing preferences, such as increasingly negative amenity values associated with an extreme heat day of a given temperature. However, we think a more natural explanation is simply that the "hot" climate counties have gotten considerably hotter – with extreme heat days becoming both hotter and more frequent – to the point where they are no longer as tolerable as they once were. For instance, the 90th percentile county over 1951-1980 averaged about two months (62 days) per year of extreme heat (daily average temperature was above 80°F (26.7°C)). That number grew to 72 days by 1991-2020.

Figure 13 repeats this exercise but for extreme cold. Panel (a) shows that the correlation across counties between extreme cold and population growth was strongly negative in the 1980s. This correlation weakened but remained negative and significant in the 1990s and 2000s (panels b and c). However, the correlation was essentially zero by the 2010s. As shown in panels (e) and

[26] We also calculate projections of population and employment based on estimates from the panel PDL model that allows for heterogeneous weather effects along the dimensions of income and historical climate. The results are shown in Online Appendix Figure A15. The projections have similar overall patterns to those of the baseline/no-heterogeneity model, but with some interesting differences. In particular, income, which tends to be higher in urban areas, plays a important role. While population is generally projected to decrease in the South relative to the North, urban areas in the South, such as Miami, Atlanta, Memphis, Raleigh-Durham, and Dallas-Fort Worth, are found to be exceptions. In addition, employment is generally projected to see relative increases in the North, but higher income counties near Chicago, Detroit, Pittsburgh, New York City, and Boise show up as exceptions.

(f), our projections point to faster population growth in historically cold counties compared to other counties. As with extreme heat, this could reflect changing preferences but a more natural interpretation is that historical cold places are seeing fewer extreme cold days over time and higher temperatures on those days, making these places relatively more attractive than in the past.

6.2.2 Aggregate Magnitude of Reallocation

To quantify the aggregate magnitude of these projected spatial reallocations of people and jobs due to climate change, we calculate the mean absolute deviation (MAD) between county population or employment growth (Δy_i) and the national average of county population or employment growth ($\bar{\Delta y}$), where growth is measured as the 30-year change in log population or employment. Note that, in the projections, average county growth is zero. In the historical regressions, average county growth is absorbed by year fixed effects, which are unobservable for future years. Thus, this MAD collapses to be simply the mean absolute value of county population (or employment) growth. We calculate the MAD for each of the three climate change scenarios, corresponding to the IPCC RCP 2.6, 4.5, and 8.5 global greenhouse gas emissions scenarios. For comparison, we also calculate the MAD for the no climate change scenario, in which the weather variables in every county are held fixed at their 1990-2020 means.

The main results, based on our baseline PDL model, are shown in panel A of Table 1. In the no climate change baseline, the MAD of county population growth is 0.75 percentage point at an annual rate. This is nearly identical to the actual mean absolute population growth over 1990 to 2020. We find that climate change increases population reallocation relative to the baseline by 0.26, 0.56, or 0.74 p.p. depending on the climate change scenario (2.6, 4.5, or 8.5, respectively). In other words, climate change is projected to increase population reallocation by between 35 and 99 percent. The projected increase in employment reallocation is similar. Specifically, we find climate change increases employment reallocation by between 0.30 and 1.07 p.p., or 29 to 103 percent, relative to the no climate change scenario. These magnitudes are large and support the contention by Partridge et al. (2017) and others that mobility likely will be a first-order channel of climate change adaptation in the United States. [27]

We can also assess whether the large projected increase in reallocation due to climate change is driven more by the projected increases in hot days or the projected decreases in cold days. To do this, first we calculate the MAD for a climate change scenario in which the two heat days variables follow the RCP 4.5 projections while the other weather variables stay at their 1991-2020 average. We then repeat this but only allowing the two cold days variables to follow the RCP 4.5 projections. The results are shown in the first two rows of panel B of Table 1. We find that the projected declines in cold and extremely cold days are more important for reallocation, especially for employment,

[27] See also Bilal & Rossi-Hansberg (2023). Using a dynamic spatial equilibrium model fitted to match reduced-form evidence of extreme weather events' effects on economic activity, they find that welfare costs of climate change would be much more concentrated absent migration, with workers in affected areas experiencing much larger losses.

than are the projected increases in hot days. For instance, allowing for just projected increases in the two hot days variables causes the MAD of population growth to increase relative to the no climate change scenario by 23%, from 0.75 to 0.92. Allowing for just projected decreases in cold days causes reallocation to go up by 57%, from 0.75 to 1.18. For employment, allowing just cold days to change as projected makes reallocation go up from 1.04 to 1.80, which is approximately equal to the reallocation from allowing all variables to change (1.77). In other words, cold days explain about three-quarters of the 75% increase in population reallocation due to climate change (1.18/.75 of the 1.31/.75 total increase) and 100% of the increase in employment reallocation due to climate change.

Lastly, we highlight the importance of the long lag process in our PDL model compared to the static model (i.e., the "No lags" model shown in Figure 6), which only accounts for contemporaneous weather effects. Following the methodology in Section 6.1, but using the static model instead of the PDL model, we obtain county-level projections of population and employment based on the RCP 4.5 scenario. The implied amount of reallocation for population and employment from the static model is shown in the last row of Panel B. The static model yields levels of reallocation very similar to the no climate change scenario. This is not surprising given that we found near-zero weather effects from the static model as shown in Figure 6.

7 Conclusion

This paper estimated how the spatial distribution of U.S. economic activity has been impacted by local climate changes in recent decades and projected how this spatial distribution could change further in the decades ahead given current climate change scenarios. First, we exploited the substantial geographic variation in weather histories across U.S. counties to estimate the historical longer-run effects of weather on local population, employment, wages, and house prices. Specifically, we estimated the full dynamic response of economic outcomes to weather shocks using panel distributed lag (DL) models covering 30 years of weather. We showed how a substantial number of lags is necessary to appropriately capture the longer-run responses to changes in weather, as contemporaneous and short-run effects are typically small and not statistically significant. Importantly, our approach captures the effects of both ex-post and ex-ante adaptation to the extent that agents have adaptive expectations.

Our historical results point to large and long-lasting effects of climate changes on local economic outcomes. This finding should inform ongoing debates about the role of internal migration as a channel of climate change adaptation. Partridge et al. (2017) stated, "While future migration will likely be a first-order driver of U.S. adaptation, we now lack key knowledge that would help us forecast its role decades in advance." These authors also argued that "with high inter-regional capital and labor mobility, migration should be a primary adaptation mechanism as households and firms relocate to their preferred location, much as U.S. population realigned from the Northeast and Manufacturing Belt to the Sunbelt and western states after World War II." We show that in fact this process already has begun. In particular, the cross-county correlation between population growth and hot climates has steadily shifted since the 1980s from being strongly positive to slightly negative.

We used the estimated panel models to project the spatial distribution of population, employment, wages, and house prices out to 2050 using historical weather augmented with county-level weather projections based on alternative climate change scenarios. The results point to sizable increases in the aggregate amounts of population and employment reallocation due to climate change. People and jobs are generally projected to move from the Sunbelt to the North and Mountain West, which would continue and accelerate the reversal of the post-World War II pattern of faster population growth in hot places.

In sum, despite evidence of a decline in U.S. internal migration over the past several decades (see, for instance, Jia et al. (2023)), our evidence suggests that population movements will nevertheless play an important role in adapting to climate change. Whether this process can be facilitated with policy and structural changes is an important issue for future research.

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A Appendix – Adaptive Expectations

In this appendix, we extend our empirical framework to incorporate adaptive expectations. When this is the case, our baseline specification accounts not just for ex-post adaptation, but also for ex-ante adaptation. To see this we extend the specification in equation (1) to allow for the possibility that expectations of future weather affects current economic outcomes:

$$\Delta y_{it} = \sum_{\ell=0}^{L} \beta_\ell w_{i,t-\ell} + \sum_{h=1}^{k} \delta_h w_{i,t}^{e,t+h} + \alpha_i + \alpha_t + \varepsilon_{it},$$

where $w_{i,t}^{e,t+h}$ is agents' expectations, as of period t, of weather in period $t+h$ in area i.

Suppose that agents in area i have standard adaptive expectations. Specifically, suppose they form expectations (forecasts) of future weather using a linear combination of past weather:

$$w_{i,t}^{e,t+h} = \sum_{\ell=0}^{L} \hat{\phi}_{i,\ell}^{h} w_{i,t-\ell} + \hat{\theta}_i^h, \text{for all } h > 0,$$

where $\hat{\theta_i^h}$ is a local fixed effect and $\hat{\phi_{i,\ell}^h}$ are weights in the linear combination of past weather. These parameters could be subjectively chosen or estimated via least squares, separately for each future horizon h. Substituting this expectations term into the previous equation yields expression (**??**) in the text:

$$\begin{aligned}
\Delta y_{it} &= \sum_{\ell=0}^{L} \beta_\ell w_{i,t-\ell} + \sum_{h=1}^{k} \delta_h \left[\sum_{\ell=0}^{L} \hat{\phi}_{i,\ell}^{h} w_{i,t-\ell} + \hat{\theta}_i^h \right] + \alpha_i + \alpha_t + \varepsilon_{it} \\
&= \sum_{\ell=0}^{L} (\beta_\ell + \sum_{h=1}^{k} \delta_h \hat{\phi_{i,\ell}^h}) w_{i,t-\ell} + (\alpha_i + \sum_{h=1}^{k} \delta_h \hat{\theta_i^h}) + \alpha_t + \varepsilon_{it} \\
&= \sum_{\ell=0}^{L} \tilde{\beta_{i,\ell}} w_{i,t-\ell} + \tilde{\alpha_i} + \alpha_t + \varepsilon_{it},
\end{aligned}$$

where $\tilde{\beta_{i,\ell}} = \beta_\ell + \sum_{h=1}^{k} \delta_h \hat{\phi_{i,\ell}^h}$ and $\tilde{\alpha_i} = \alpha_i + \sum_{h=1}^{k} \delta_h \hat{\theta_i^h}$.

B Appendix – A Simple Spatial Equilibrium Model

In this appendix, we first introduce a simple spatial equilibrium model in the spirit of Rosen (1979) and Roback (1982) to illustrate the impact of climate change on local economies. Our framework builds on the model of Hsieh & Moretti (2019), but in which we introduce two types of households: workers and non-workers, which, for simplicity, we will hereafter refer to as "retirees."[28]

[28]While retirees account for roughly 50 percent of the U.S. working-age population not in the labor force, other reasons are also leading those of working age to opt out of the labor market, such as disabilities, attending school,

This distinction will be useful in interpreting the different empirical responses of employment and population to weather variables below. Absent this distinction, there would be no difference between employment and population, as is the case in most models in the literature that the population in a location is fully employed. In addition to deciding in which regions to live, households choose their consumption of traded and nontraded goods (e.g., housing). [29] Workers receive wage income derived from inelastically supplying one unit of labor to firms in their location. Retirees receive a fixed income from the federal government ("retirement benefits"). We assume that workers and retirees are hand-to-mouth agents and therefore fully consume their income each period. In each location, perfectly competitive firms produce a costlessly traded good subject to local productivity shocks. Similarly, firms in the housing sector produce housing services using a combination of traded goods and land. Both types of households choose where to locate based on their utility. By impacting local productivity and amenities, climate changes affect local economies through household consumption, production, and location decisions (see, also, Desmet & Rossi-Hansberg (2015), Desmet et al. (2018), Cruz & Rossi-Hansberg (2021), Nath (2020)). We now describe the different aspects of the model and the channels through which climate changes impact local economies.

B.1 Households

The economy is composed of a continuum of locations $l \in [0, N]$ populated by two types of households, workers and retirees, indexed by $i = \{w, r\}$. In each location, the continuum of households $j \in [0, 1]$ of type i are assumed to be risk neutral with preferences $\varepsilon^i_{j,l} u(c^i_l, h^i_l)$, where

$$u(c^i_l, h^i_l) = \left(A_l (c^i_l)^\alpha (h^i_l)^{1-\alpha}\right)$$

and c^i_l is the consumption of a traded good, h^i_l is the consumption of a nontraded good (i.e., housing), and A_l denotes local amenities. Note that we assume that workers and retirees have the same preferences over local amenities. We assume that A_l is a stochastic variable that reacts to changes in climate, as specified below. In addition, preferences are also subject to an idiosyncratic preference shock, $\varepsilon^i_{j,l}$, that influences households' preference for a given location. The shock is assumed to follow a Fréchet distribution with shape parameter θ. We let L^i_l be the measure of type i locating in each location l. Since as in most of the literature we abstract from variations in local unemployment rates, the population of workers will also reflect local employment.[30]

We assume that workers and retirees are hand-to-mouth agents and therefore fully consume their income each period. Irrespective of location, retirees receive a transfer y (in unit of the traded good) from the federal government financed through a labor income tax. They spend this income

or caring for family members, among others.

[29]We consider nontraded goods as representing housing even though, for simplicity, we abstract from relevant features in housing markets that are not central to our analysis.

[30]See Kline & Moretti (2013) for a spatial equilibrium model with labor search frictions and unemployment.

on the consumption of the traded good and on housing: $c_l^r + p_l h_l^r = y^r$, where p_l is the relative price of housing. In contrast, workers supply one unit of labor inelastically to firms in location l at wage rate ω_l. Like retirees, they spend their after-tax income on the consumption of the traded good and housing: $c_l^w + p_l h_l^w = (1-\tau)\omega_l = y_l^w$.

Given the absence of saving and investment, households maximize their per-period utility subject to their budget constraint. Thus, the optimality conditions dictate that workers and retirees both allocate a fraction α and $1-\alpha$ of their income to expenditures on the traded good and housing

$$\begin{aligned} c_l^w &= \alpha y_l^w \qquad\qquad p_l h_l^w = (1-\alpha) y_l^w \\ c_l^r &= \alpha y^r \qquad\qquad p_l h_l^r = (1-\alpha) y^r. \end{aligned}$$

B.2 Production of the traded good

Firms in each location produce the traded good using local labor, L_l:

$$Y_l = z_l L_l^{\phi}.$$

Profit maximization yields that following labor demand expression:

$$L_l = \left(\phi \frac{z_l}{w_l}\right)^{\frac{1}{1-\phi}}.$$

B.3 Housing

Each location is endowed with an exogenous amount of land, T_l, which can be used in combination with traded goods to produce housing services:

$$H_l = \gamma^{-\gamma} \left(Y_l^d\right)^{\gamma} (T_l)^{1-\gamma},$$

where Y_l^d is the amount of traded goods used. From profit maximization, the supply of housing services can be written as

$$H_l = T_l p_l^{\eta}$$

where $\eta = \frac{\gamma}{1-\gamma}$ is the housing supply elasticity.

B.4 Climate change

Consider a vector $\mathcal{W}_{l,t}$ denoting a set of characteristics representing local climate (frequency of cold days, frequency of hot days, precipitation, etc.). Let $\mathcal{W}_l^*$ denote the ideal, nonstochastic, set of climate characteristics for location l and let $d(\mathcal{W}_{l,t}, \mathcal{W}_l^*)$ be a measure of distance between $\mathcal{W}_{l,t}$ and $\mathcal{W}_l^*$. We assume that local productivity and amenities are functions of local climate:

$$x_{l,t} = (1 - \Psi_x(d(\mathcal{W}_{l,t}, \mathcal{W}_l^*)))\, \widetilde{x}_{l,t} \qquad \text{for } x \in \{z, A\}$$

where $\Psi_x : R_{\geq 0} \rightarrow [0, 1)$ is a damage function that increase with the distance between current and optimal climate characteristics, while a tilde indicates the pre-damage level of a variable. As in Hsiang (2016), local climate characteristics are a function of local climate via the distribution $\mathcal{W}_{l,t} \backsim G(C_{l,t})$. By impacting local climate differently depending on location (e.g., elevation, latitude, longitude, or coastal proximity), global climate change increases local damages to different degrees. Higher damages reduce productivity and amenities.

B.5 Spatial equilibrium

Households decide where to live by maximizing the indirect utility of living in different locations, V_l^i, given the realization of the idiosyncratic preference shock. This maximization yields the following expression

$$L_l^i = \frac{(V_l^i)^\theta}{\sum_k (V_k^i)^\theta} = \left(\frac{V_l^i}{V^i}\right)^\theta$$

such that the decision to live in a given location depends on the indirect utility in this location relative to all other ones ($V^i \equiv \sum_k (V_k^i)^\theta$), where the indirect utility is given by

$$V_l^i = \left(\psi A_l \frac{y_l^i}{p_l^{1-\alpha}}\right)$$

with $\psi \equiv \alpha^\alpha (1-\alpha)^{(1-\alpha)}$. Thus, higher income, higher amenities, and lower house prices each increases the indirect utility of living in location l.

Using this expression, the supply of type i in location l becomes

$$L_l^i = \left(\frac{\psi A_l \frac{y_l^i}{p_l^{1-\alpha}}}{V^i}\right)^\theta .$$

Equating the demand and supply of workers in each location, we further get the population of workers in location l

$$L_l^w = \left(\psi A_l (1-\tau) \phi \frac{z_l}{p_l} \frac{1}{V^w}\right)^{\frac{1}{1-\phi+1/\theta}} . \tag{B1}$$

Since retirees by definition are out of the labor force, their population in location l is given by

$$L_l^r = \frac{\left(\psi A_l \frac{y^r}{p_l^{1-\alpha}}\right)^\theta}{(V^r)^\theta} . \tag{B2}$$

Note that while the sum of $L_l^w$and L_l^r represent the total population of a location, total employment is given by L_l^w We use this distinction below to interpret our empirical results through the lens of the model.

Thus, climate change can impact the population through different channels. By reducing amenities, climate change will induce the populations of workers and retirees to fall. However, for workers, a reduction in productivity would be an additional factor directly contributing to a lower population. Note that climate change will have a greater impact on population the lower is $1/\theta$, i.e., the lower are preferences for a given location. In this case, more workers and retirees are willing to relocate to other locations given climate-induced changes in productivity and amenities. Equations (B1) and (B2) will be useful in accounting for our empirical responses to climate change below in terms of its impact on amenities and productivity.

Finally, climate changes can affect house prices through changes in productivity and amenities, as shown by the following equilibrium condition

$$p_l = \left[\frac{(1-\alpha)(L_l^w(1-\tau)\omega_l + L_l^r y)}{T_l}\right]^{\frac{1}{\eta}}. \tag{B3}$$

First, holding local population fixed, climate changes would lower house prices through declines in productivity and wages. In addition, house prices would tend to decline with reductions in workers' or retirees' populations (via lower productivity or amenities). How much local climate changes impact house prices versus population is regulated by the housing supply elasticity, η.

B.6 Amenity and Productivity

The log values of amenities (A_{lt}) and productivity (Z_{lt}) in the text can be derived from the equilibrium equations for worker population (L_{lt}^w) and non-worker population (L_{lt}^r), equations (B1) and (B2), respectively. Specifically, taking the log of both sides of equation (B2) and solving for $log(A_{lt})$ yields:

$$log(A_{lt}) = (1/\theta)log(L_{lt}^r) + (1-\alpha)log(p_{lt}) + f_t^r, \tag{B4}$$

where $f_t^r = log(V_t^r) - log(y_t^r) - log(\psi)$.

Similarly, taking the logs of both sides of equation (B1), solving for $log(z_{lt})$, and using the equation above for $log(A_{lt})$, we get:

$$\begin{aligned} log(z_{lt}) &= (1-\phi+1/\theta)log(L_{lt}^w) - (1/\theta)log(L_{lt}^r) + \alpha log(p_{lt}) - f_t^r + f_t^w \\ &= (1-\phi+1/\theta)log(L_{lt}^w) - (1/\theta)log(1-L_{lt}^w) + \alpha log(p_{lt}) - f_t^r + f_t^w, \end{aligned} \tag{B5}$$

where $f_t^w = log(V_t^w) - log(\psi) - log(1-\tau) - log(\phi)$.

Table 1: Effect of Climate Changes on Spatial Reallocation

Mean Absolute Deviation
between County Growth and National Average County Growth
(2020 - 2050, Annualized, Percentage Points)

Panel A. Main Results

	Population	Employment
No climate change scenario	0.75	1.04
RCP 2.6 scenario	1.01	1.34
RCP 4.5 scenario	1.31	1.77
RCP 8.5 scenario	1.49	2.11

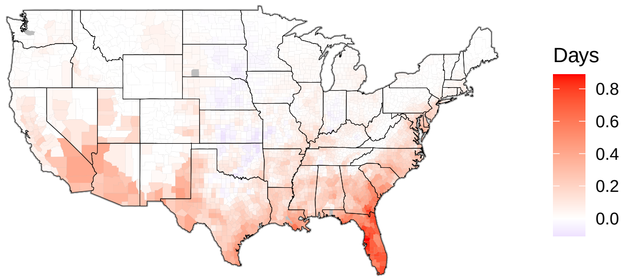
Panel B. Additional Scenarios

	Population	Employment
Climate change only from hot days (RCP 4.5)	0.92	1.16
Climate change only from cold days (RCP 4.5	1.18	1.80
RCP 4.5 using Static model	0.77	1.04

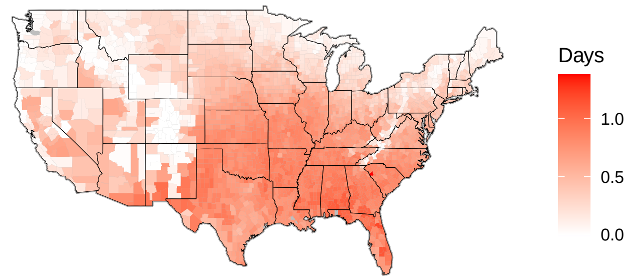
Figure 1: Historical and Projected Temperature Trends across U.S. Counties

Yearly Trend in # of Days with Daily Average Temperature Above 80°F (26.7°C)

(a) 1951-2020

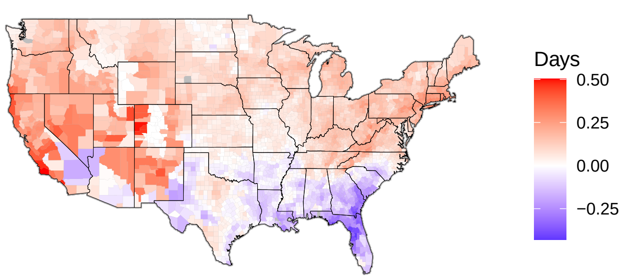


(b) 2021-2050

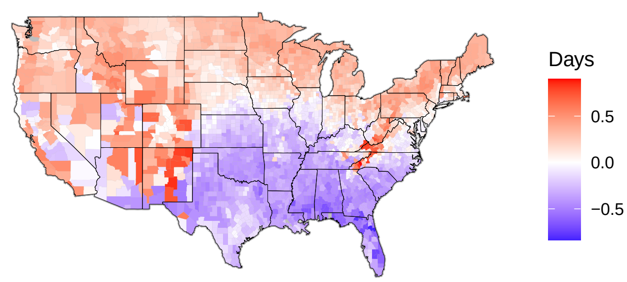


Yearly Trend in # of Days with Daily Average Temperature 70-80°F (21.1-26.7°C)

(c) 1951-2020

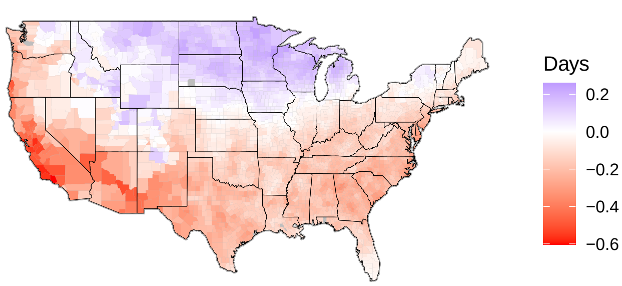


(d) 2021-2050

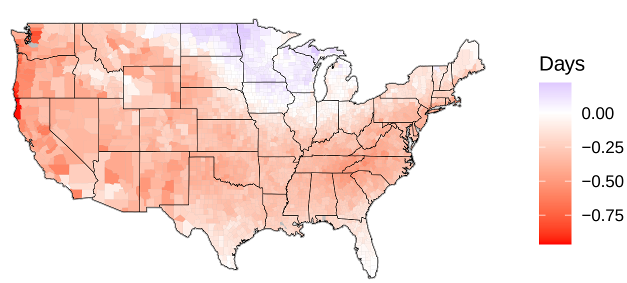


Yearly Trend in # of Days with Daily Average Temperature 20-50°F (−6.7-10°C)

(e) 1951-2020

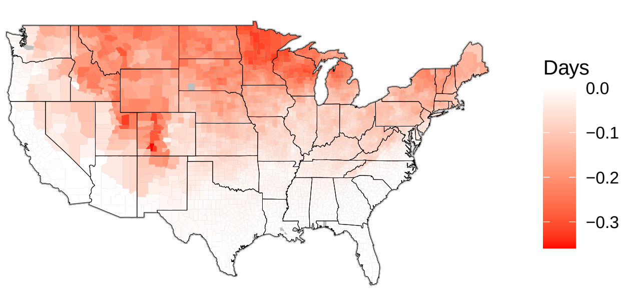


(f) 2021-2050

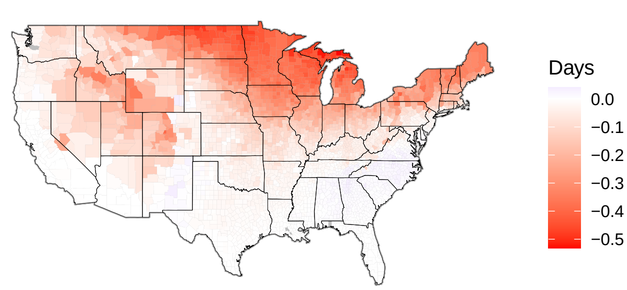


Yearly Trend in # of Days with Daily Average Temperature Below 20°F (−6.7°C)

(g) 1951-2020



(h) 2021-2050

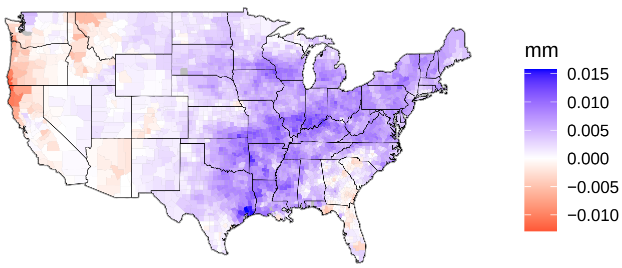


Notes: See notes after Figure 2.

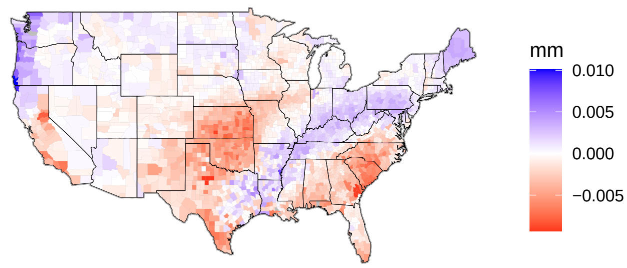
Figure 2: Historical and Projected Precipitation Trends across U.S. Counties

Yearly Trend in Average Daily Precipitation

(a) 1951-2020

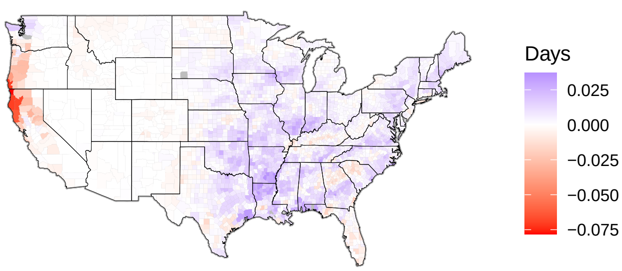


(b) 2021-2050

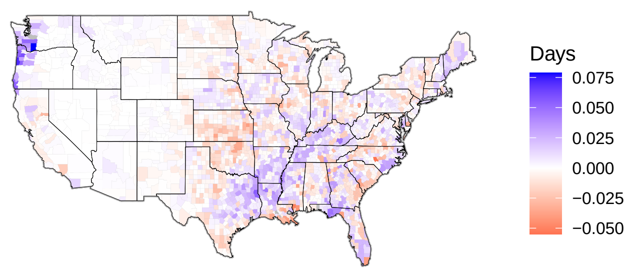


Yearly Trend in # of Days with Extreme Precipitation

(c) 1951-2020

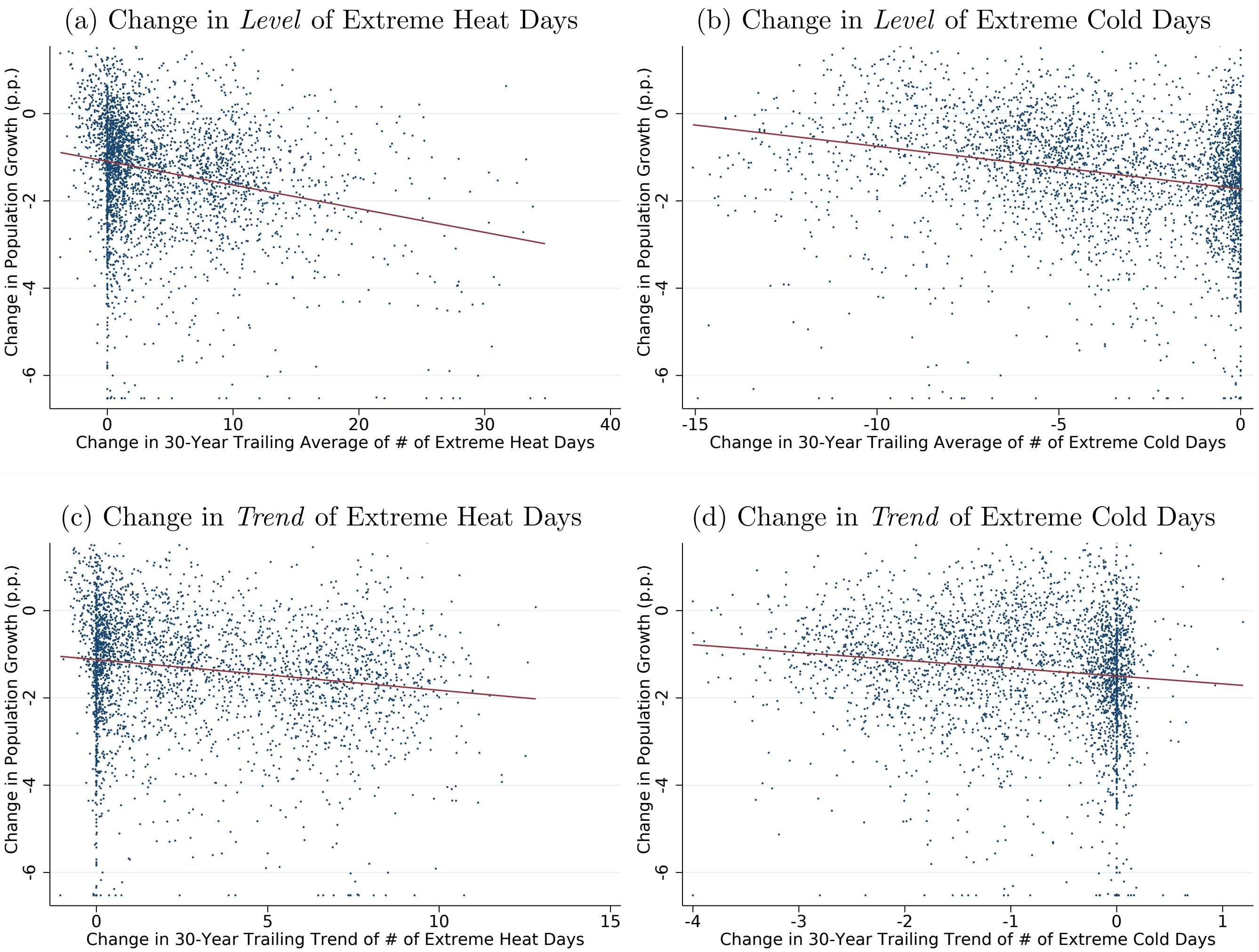


(d) 2021-2050



Notes: Each map shows the estimated yearly linear trend in the indicated weather variable over the indicated time span for each county in the contiguous United States. The 1951-2020 trends are based on county-level daily historical weather data provided by the National Centers for Environmental Information (NCEI). The 2021-2050 trends are based on the down-scaled county-level projections from Hsiang et al. (2017) associated with the IPCC RCP 4.5 global emissions scenario.

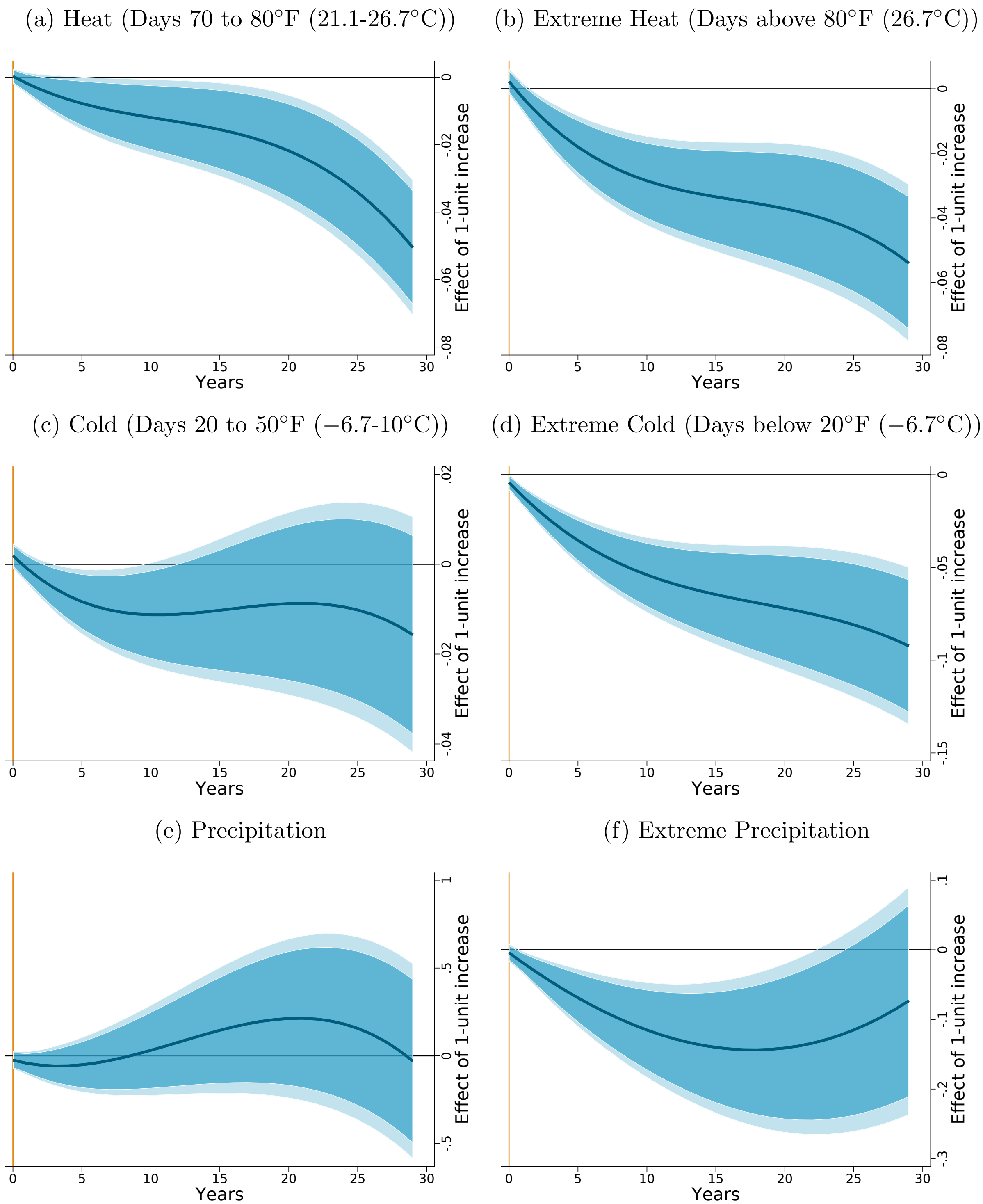
Figure 3: Cross-County Relationship between Change in Population Growth and Change in Level or Trend of Extreme Temperature Days 1980 to 2020



Notes: Each panel displays a scatter plot, where each dot represents a single county. In both panels, the y-axis values are the change (in percentage points) in the county's population growth rate over the period 1980 to 2020. To reduce noise stemming from idiosyncratic transitory shocks to population growth at these endpoints, population growth in 1980 and 2020 is measured using a 10-year trailing average and winsorized at 1st and 99th percentiles. We drop counties with zero extreme heat days over 1951-2020. In panel A, the x-axis values are the 1980 to 2020 change in the 30-year trailing *average* of the number of extreme heat days in the county (i.e., the average annual number of extreme heat days over the period 1991-2020 minus that over the period 1951-1980). In panel B, the x-axis values are the 1980 to 2020 change in the 30-year trailing *trend* of the number of extreme heat days in the county (i.e., the average annual change in the number of extreme heat days over the period 1991-2020 minus that over the period 1951-1980). The red line in each panel is a linear OLS regression fit line.

Figure 4: Impulse Response of Population to Weather

Third-Order Polynomial Distributed Lag Model



(a) Heat (Days 70 to 80°F (21.1-26.7°C))

(b) Extreme Heat (Days above 80°F (26.7°C))

(c) Cold (Days 20 to 50°F (−6.7-10°C))

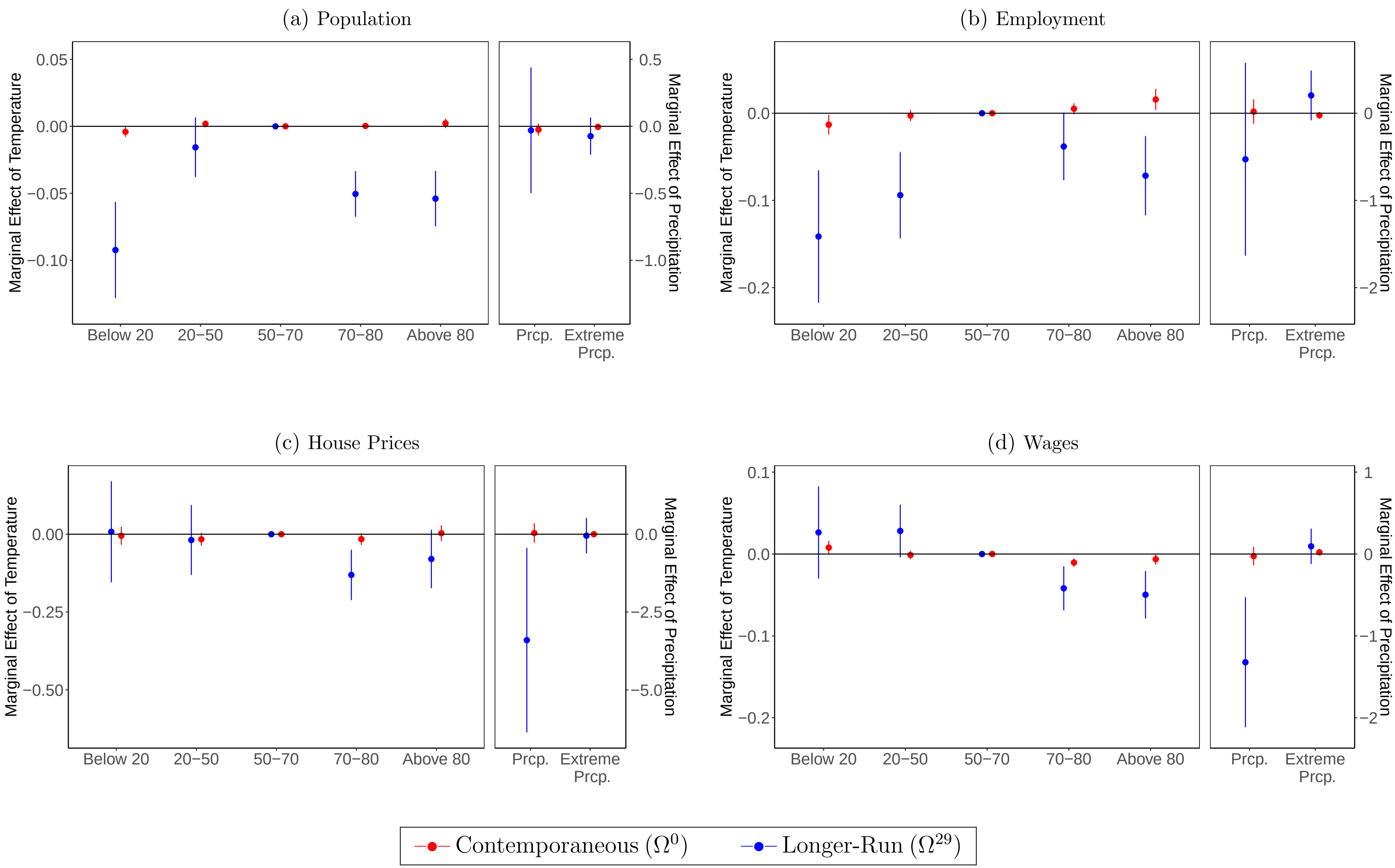
(d) Extreme Cold (Days below 20°F (−6.7°C))

(e) Precipitation

(f) Extreme Precipitation

Notes: These plots show the estimated impulse response function of the indicated weather variable for the indicated outcome. The underlying regression includes county and year fixed effects. Standard errors are two-way clustered by county and by year. The inner shaded region shows the 90 percent confidence interval, and the outer lighter shaded region shows the 95 percent confidence intervals.

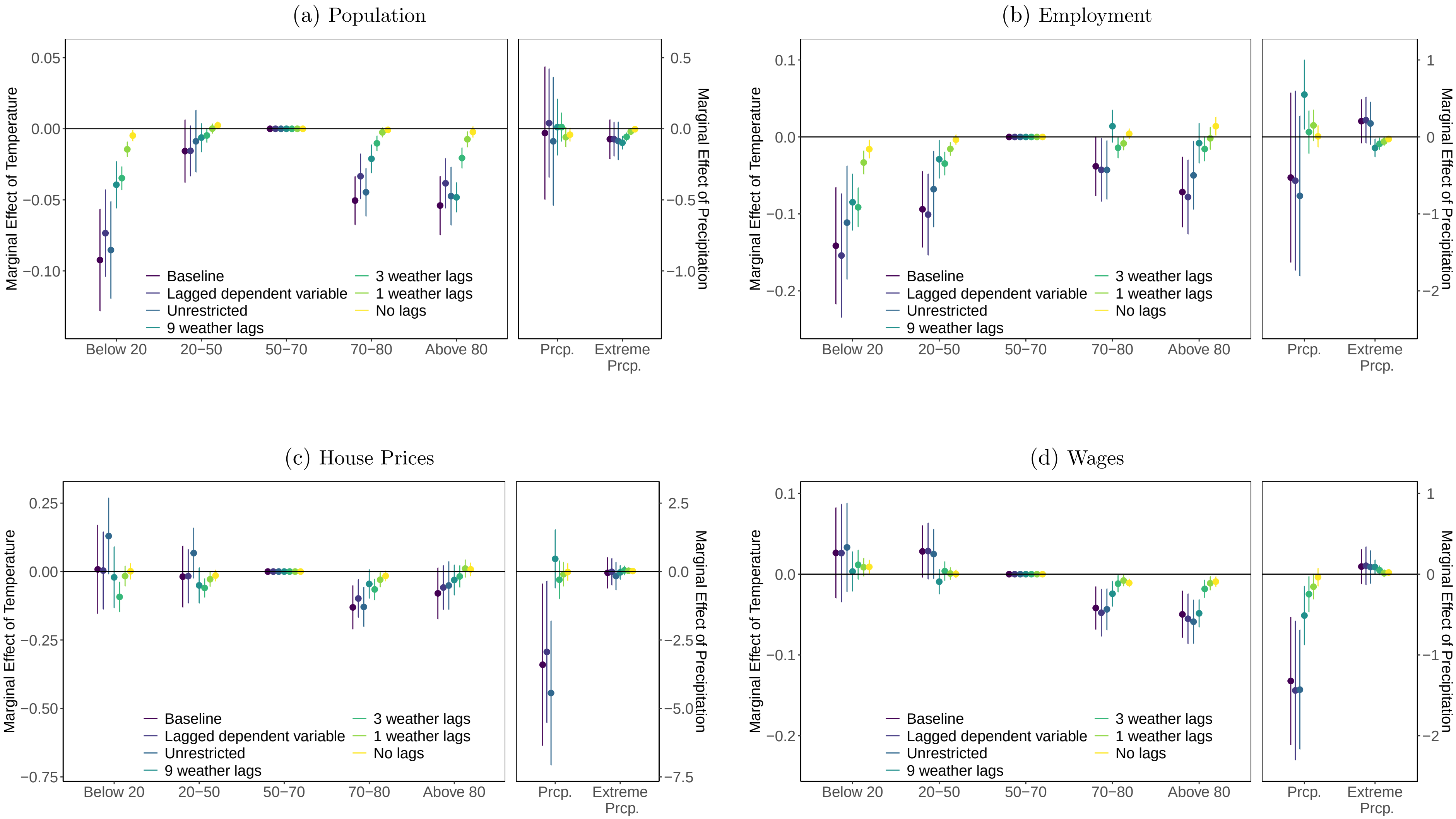
Figure 5: Contemporaneous and Longer-Run Marginal Effects of Weather



Notes: These plots show the estimated contemporaneous and longer-run marginal effect of the weather variable indicated on the x-axis on the level of the outcome variable indicated in the panel heading. The underlying regression includes county and year fixed effects. Standard errors are two-way clustered by county and by year. The range shown above and below the marker displays the 90 percent confidence interval.

Figure 6: Longer-Run Marginal Effects of Weather

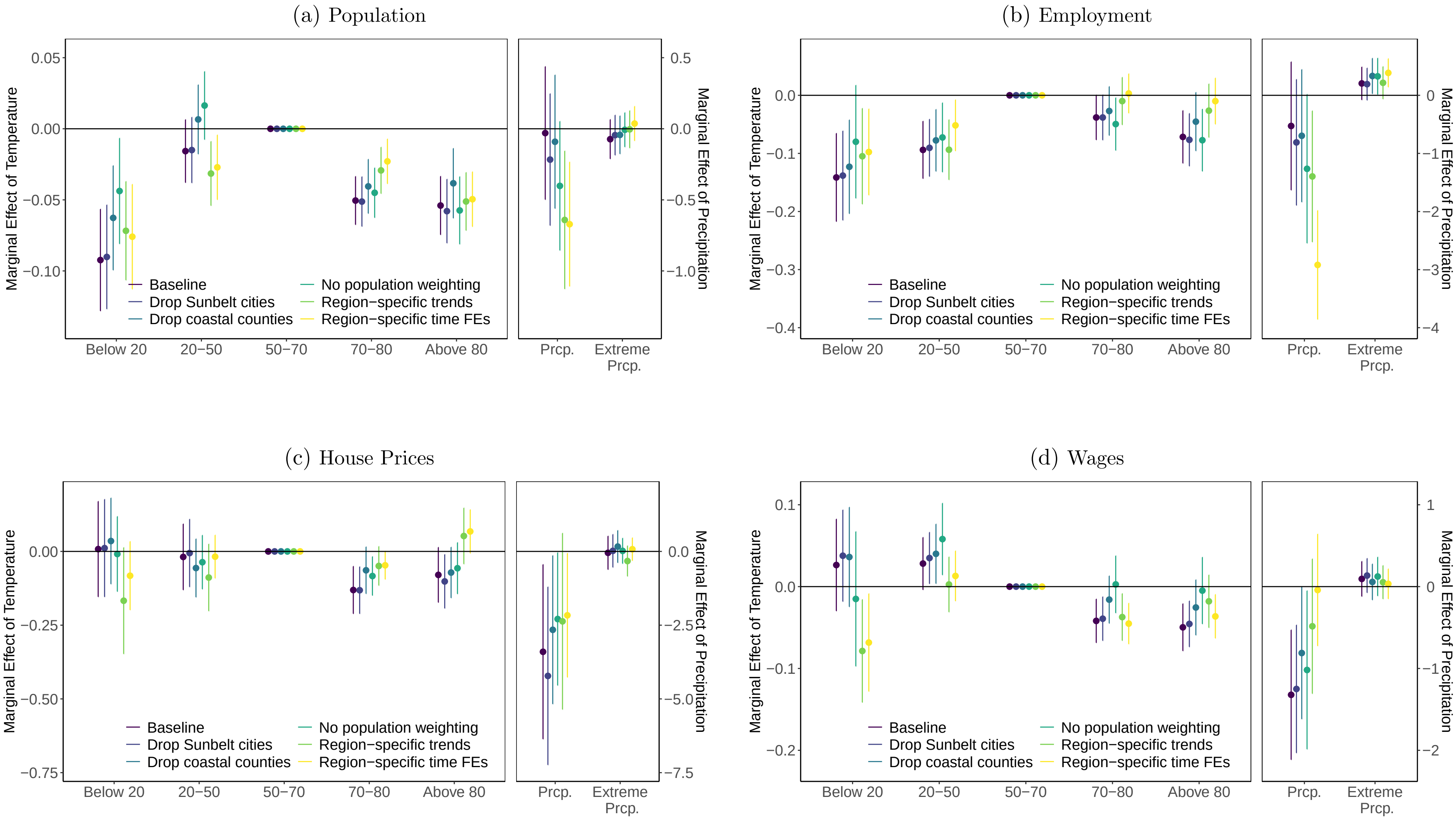
Alternative Specifications



Notes: Each plot shows the estimated longer-run marginal weather effects based on the baseline regression specification as well as several alternative specifications. Each series (color) corresponds to a different specification. The dots for each series show the longer-run (30-year) marginal effect of the weather variable indicated on the x-axis on the level of the outcome variable indicated in the panel heading. The range shown above and below the marker displays the 90 percent confidence interval based on standard errors that are two-way clustered by county and by year.

Figure 7: Longer-Run Marginal Effects of Weather

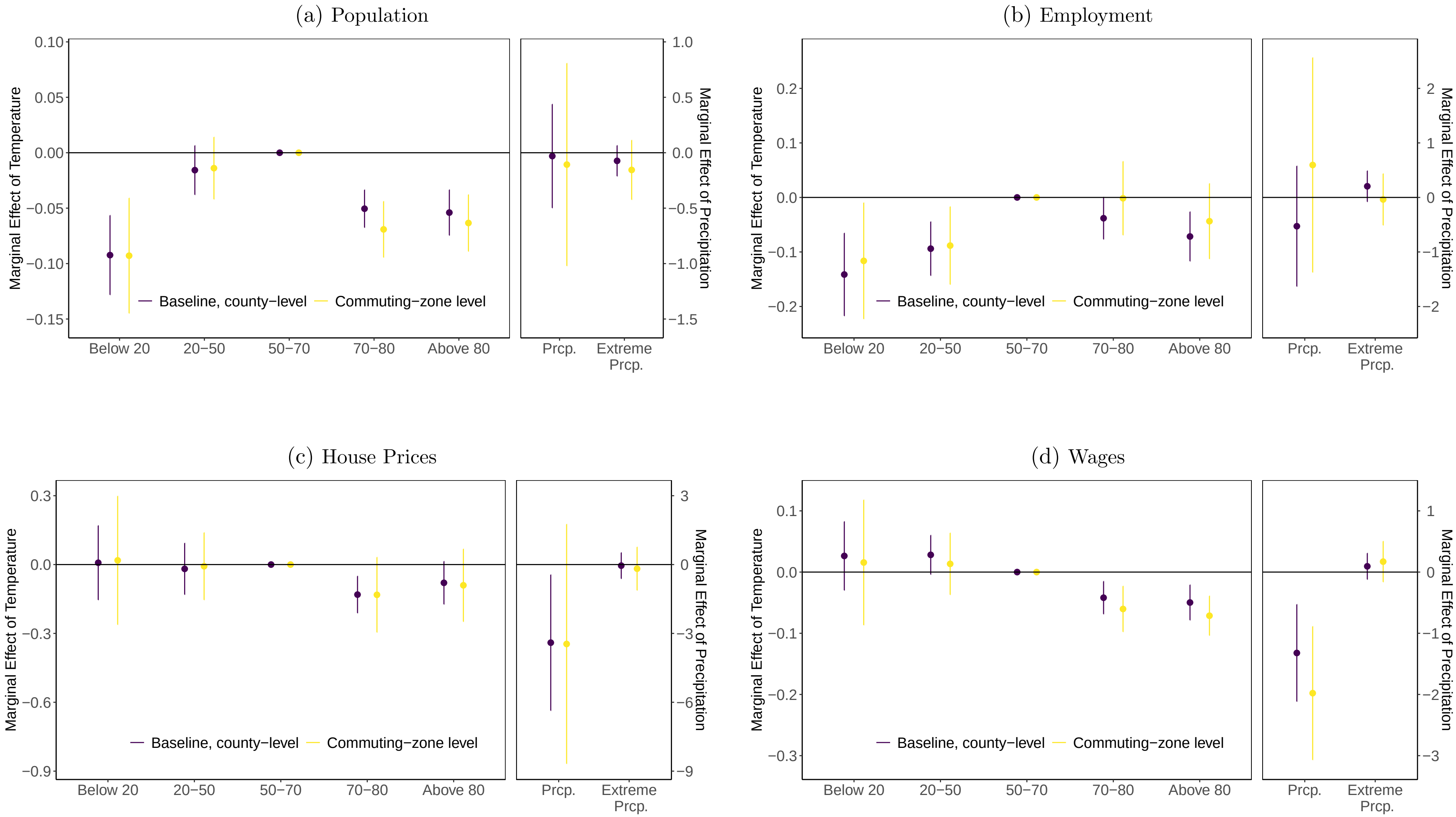
Alternative Specifications, Samples, and Weighting



Notes: Each plot shows the estimated longer-run marginal weather effects based on the baseline specification and sample as well as those based on various alternative specifications or sample restrictions. Each series (color) corresponds to a different specification (using baseline sample) or sample restriction (using baseline specification). The dots for each series show the marginal effect of the weather variable indicated on the x-axis on the level of the outcome variable indicated in the panel heading. The range shown above and below the marker displays the 90 percent confidence interval based on standard errors that are two-way clustered by county and by year.

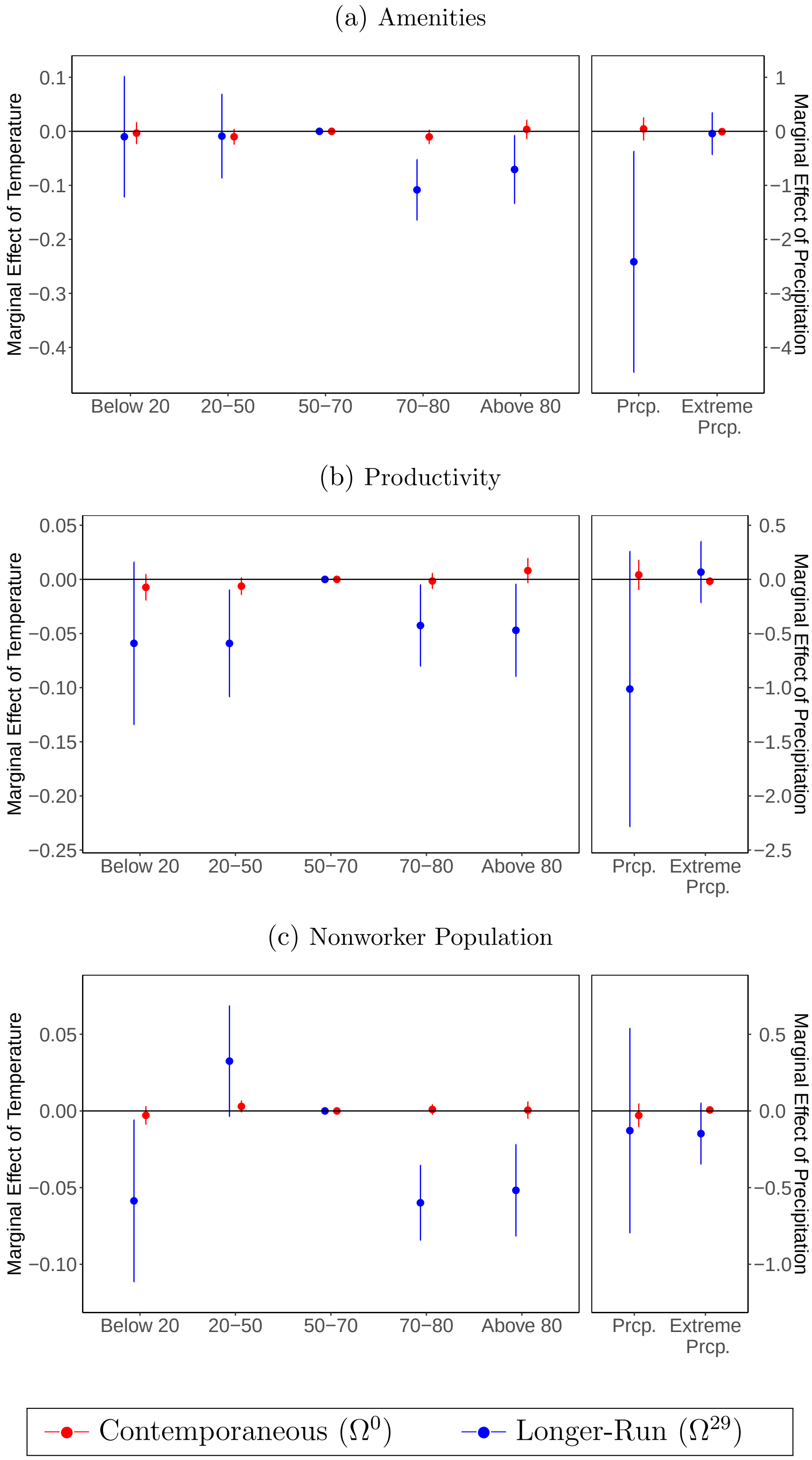
Figure 8: Longer-Run Marginal Effects of Weather

Based on Data Aggregated to Commuting Zone Level



Notes: Each plot shows the estimated longer-run marginal weather effects using county level data as well as those using commuting zone (CZ) level data. The county-level regressions include county and year fixed effects. The CZ-level regressions include CZ and year fixed effects. Standard errors for the county level regressions are two-way clustered by county and by state-year, while CZ-level standard errors are two-way clustered by CZ and by year. The range shown above and below the markers display the 90 percent confidence interval.

Figure 9: Marginal Effects of Weather on Amenities and Productivity

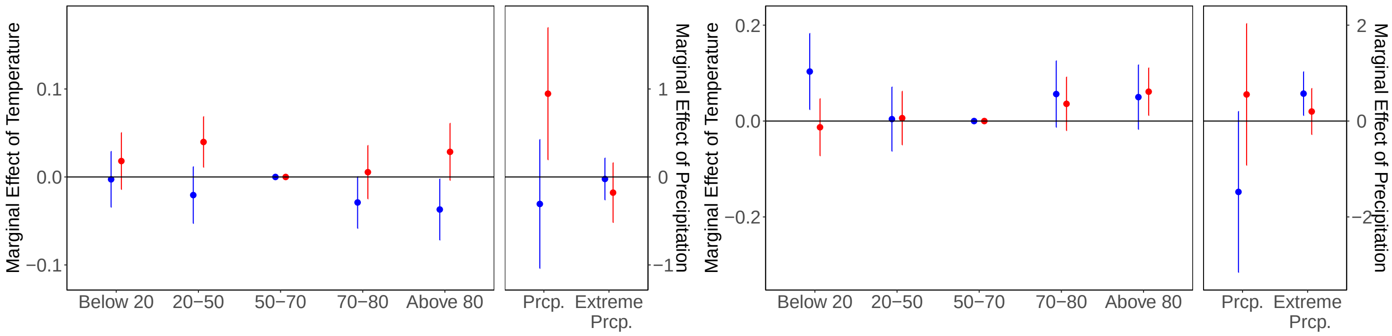


Notes: These plots show the estimated contemporaneous and longer-run marginal effect of the weather variable indicated on the x-axis on the level of the outcome variable indicated in the panel heading. The underlying regression includes county and year fixed effects. Standard errors are two-way clustered by county and by year. The range shown above and below the marker displays the 90 percent confidence interval.

Figure 10: Longer-Run Effects Allowing for Heterogeneity

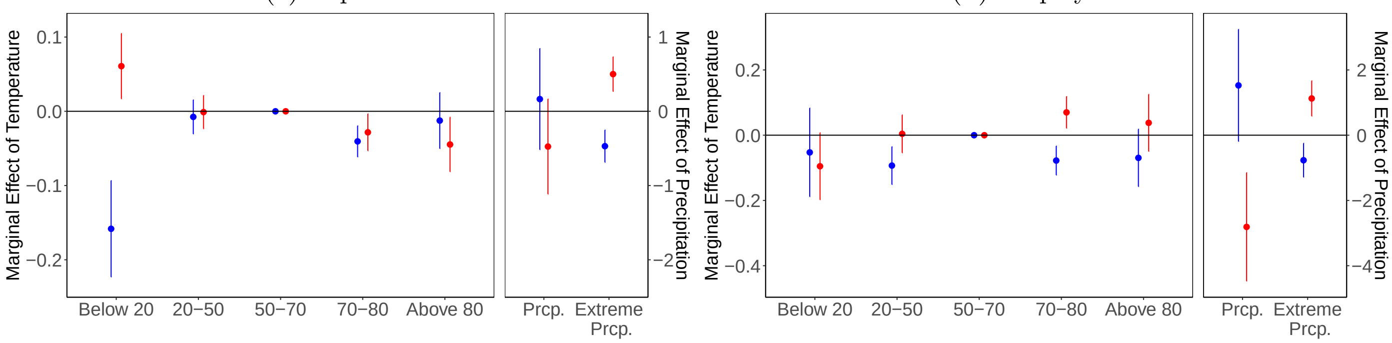
Splitting counties by whether 1969-2020 mean income p.c. is in
top (–●–) or **bottom** (–●–) tercile

(a) Population (b) Employment



Splitting counties by whether 1951-2020 mean weather (for each weather variable) is
above (–●–) or **below** (–●–) median

(c) Population (d) Employment



Splitting counties by whether belief that global warming is affecting
weather is in **top** (Red) or **bottom** (Blue) tercile

(e) Population (f) Employment

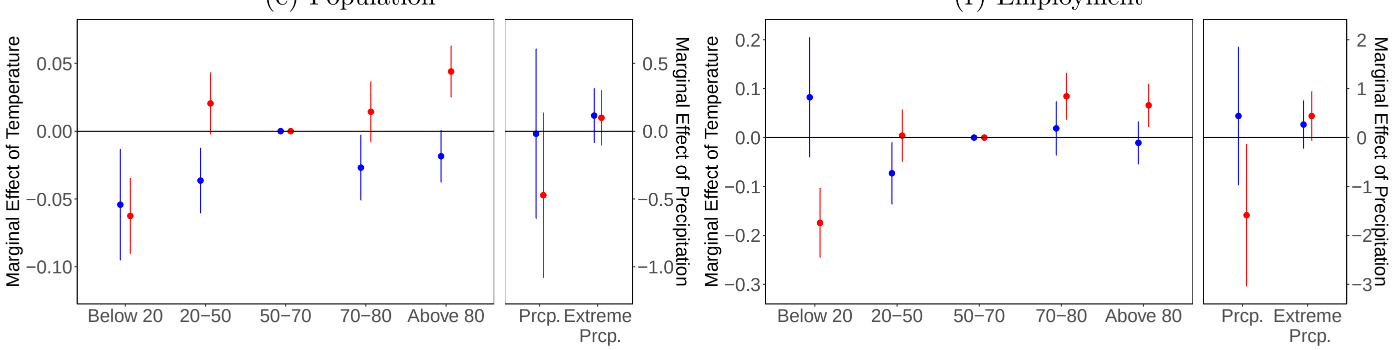
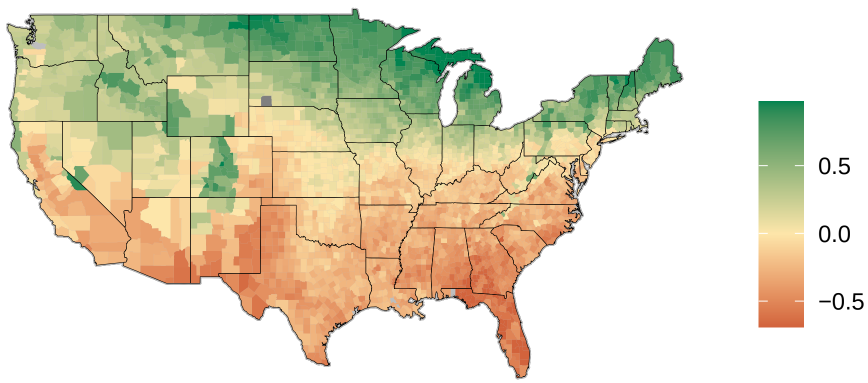


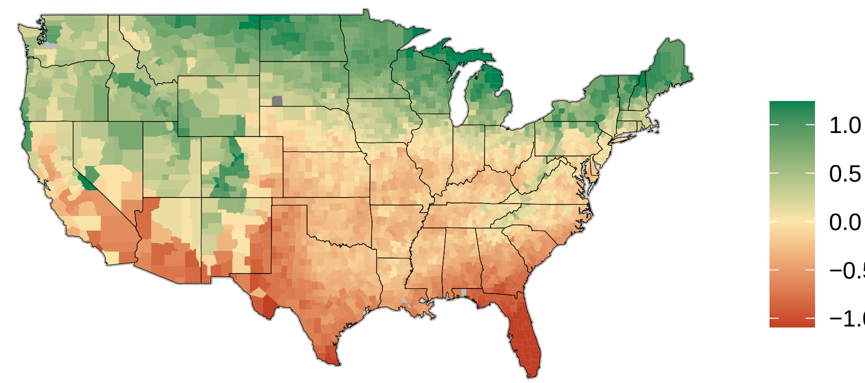
Figure 11: Projected Changes in Spatial Distribution of U.S. Economic Activity from 2020 to 2050

Due to Projected Climate Changes, Based on Basic Third-Order PDL Model and RCP 4.5 Scenario

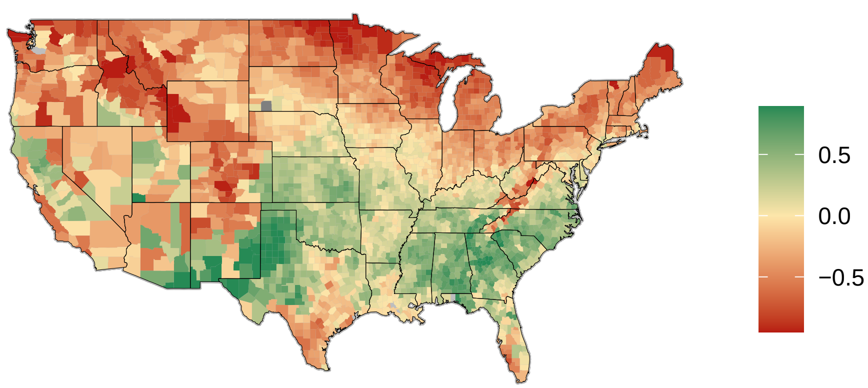
(a) Population



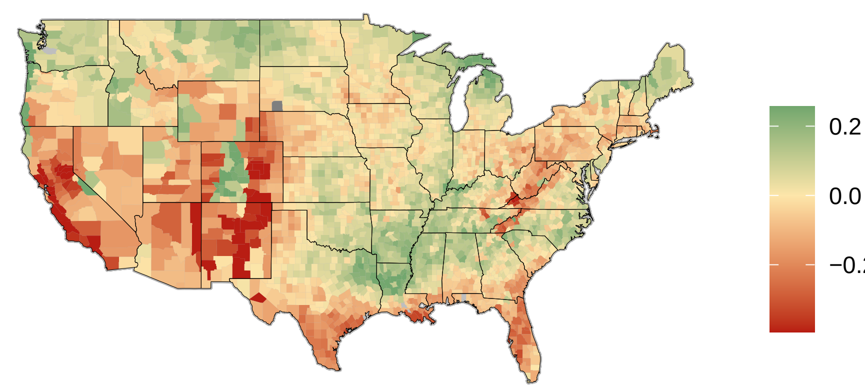
(b) Employment



(c) House Prices

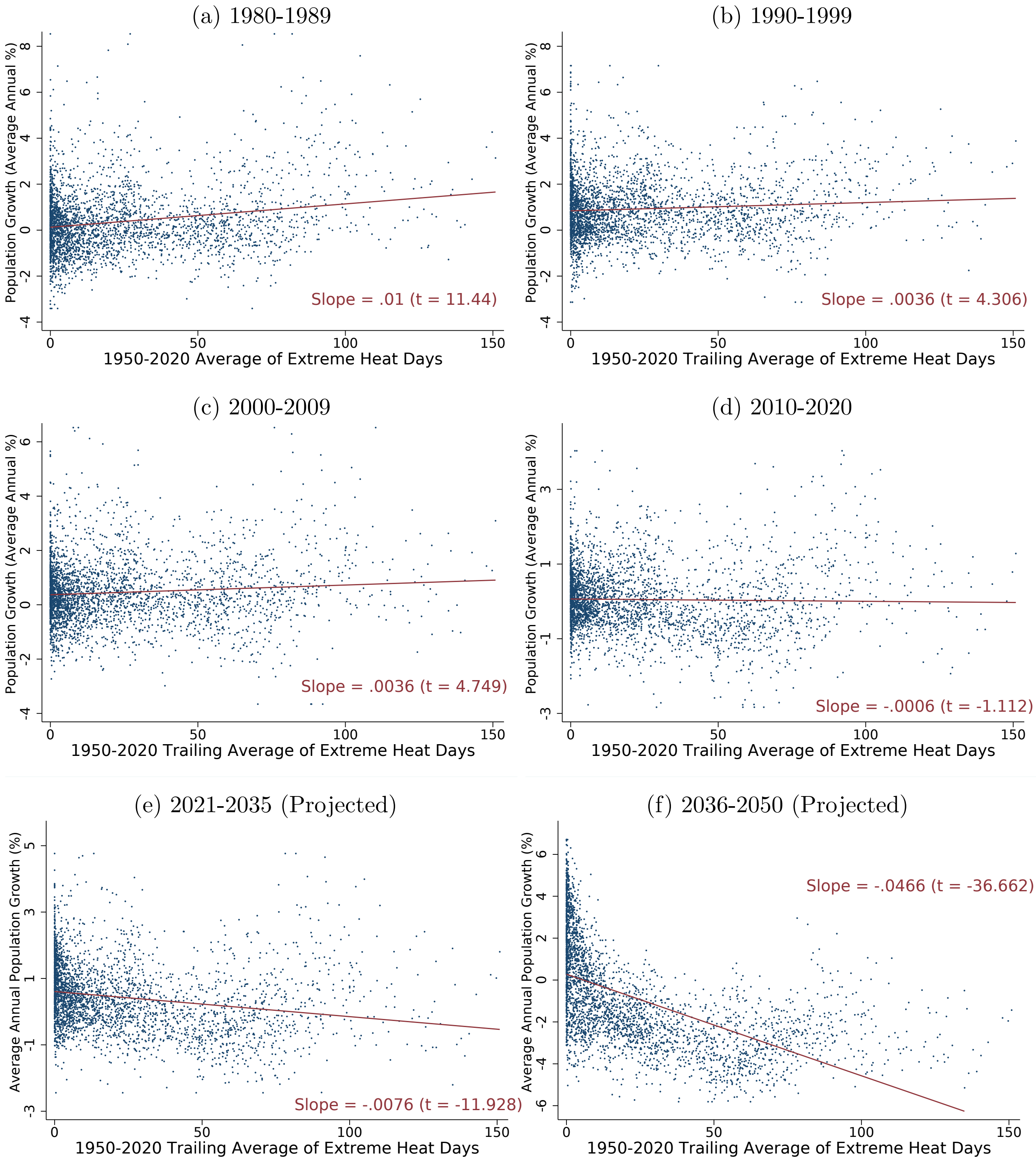


(d) Wages



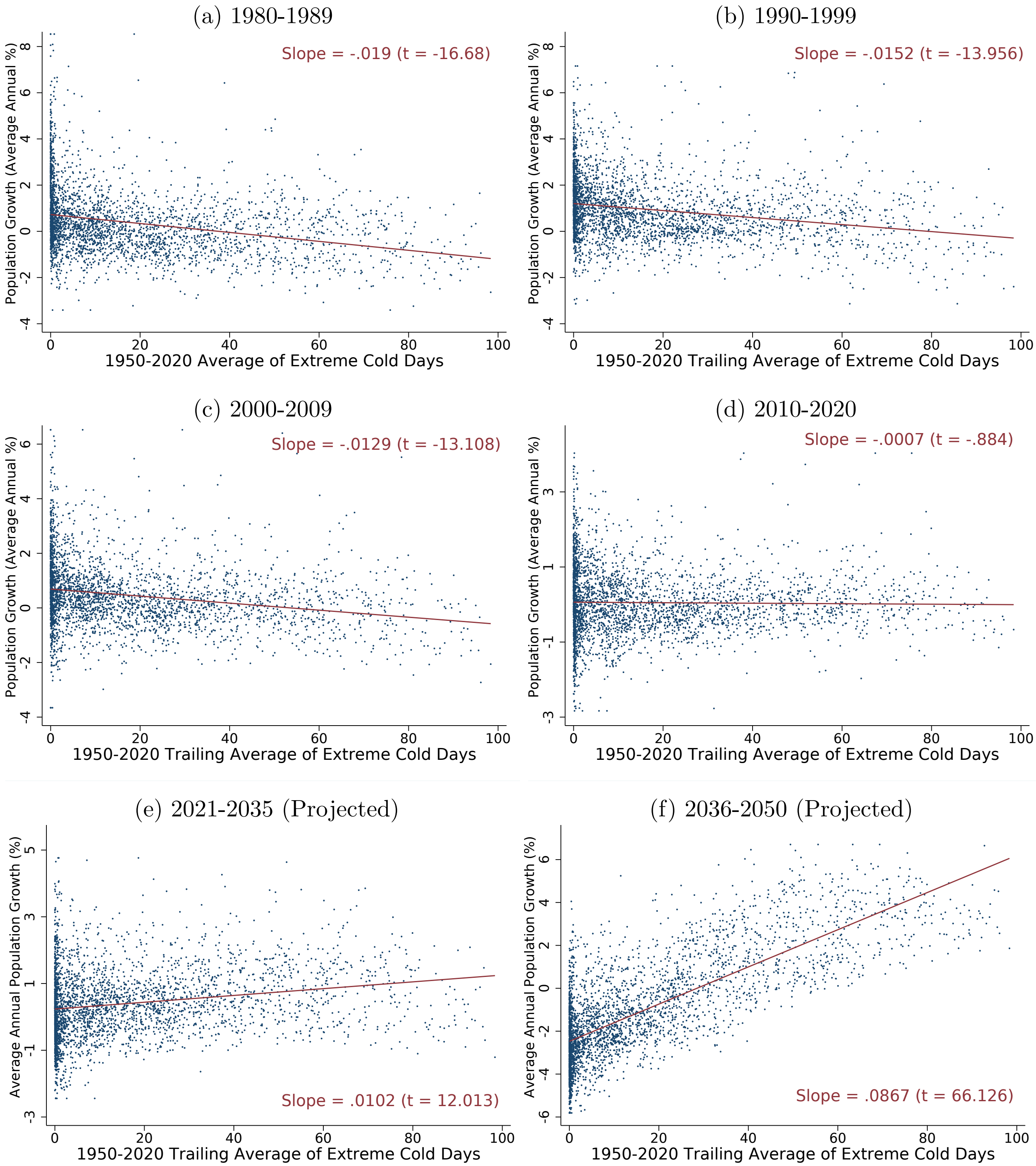
Notes: Each map shows the projected change in the log of the indicated outcome between 2020 and 2050 due to climate change (i.e., $\Delta \widehat{y_{i,2020-50}^{CC,0}}$ from equation). The units are changes in log values, so 1.0 (-1.0) corresponds to doubling (halving) of the level of the outcome.

Figure 12: Cross-County Relationship between Population Growth and Extreme Heat



Notes: Each panel displays a scatter plot, where each dot represents a single county. The y-axis shows the county's average annual population growth rate over the indicated period. The x-axis shows the 30-year trailing *average* of the number of extreme heat days in the county as of the start of the period. The red line in each panel is a linear OLS regression fit line. The slope estimate and its t-statistic are displayed.

Figure 13: Cross-County Relationship between Population Growth and Extreme Cold



Notes: Each panel displays a scatter plot, where each dot represents a single county. The y-axis shows the county's average annual population growth rate over the indicated period. The x-axis shows the 30-year trailing *average* of the number of extreme cold days in the county as of the start of the period. The red line in each panel is a linear OLS regression fit line. The slope estimate and its t-statistic are displayed.

Online Appendix A – Not For Publication

Table A1: Population, Employment, Wage, & House Price Responses to Weather

Polynomial Distributed Lag Model (3rd Order)

	(1) Population	(2) Employment	(3) Wages	(4) House Prices
Contemporaneous Effects:				
Number of days below 20F	-0.00408	-0.0131	0.00782	-0.00500
	[0.063]	[0.052]	[0.111]	[0.772]
Number of days between 20 and 50F	0.00188	-0.00272	-0.00116	-0.0162
	[0.192]	[0.475]	[0.695]	[0.184]
Number of days between 70 and 80F	0.000289	0.00515	-0.0104	-0.0158
	[0.805]	[0.161]	[0.000]	[0.155]
Number of days temp above 80F	0.00226	0.0158	-0.00632	0.00337
	[0.266]	[0.029]	[0.110]	[0.824]
Daily precipitation	-0.0244	0.0189	-0.0252	0.0377
	[0.353]	[0.822]	[0.708]	[0.839]
Number of days with extreme precipitation	-0.00420	-0.0244	0.0212	0.000995
	[0.513]	[0.256]	[0.274]	[0.982]
Sum of Contemp. & Lagged Effects:				
Number of days below 20F	-0.0923	-0.141	0.0264	0.00791
	[0]	[.002]	[.438]	[.9360]
Number of days between 20 and 50F	-0.0157	-0.0940	0.0282	-0.0187
	[.242]	[.002]	[.146]	[.783]
Number of days between 70 and 80F	-0.0505	-0.0381	-0.0419	-0.131
	[0]	[.102]	[.01]	[.007]
Number of days above 80F	-0.0540	-0.0716	-0.0497	-0.0795
	[0]	[.009]	[.004]	[.159]
Daily precipitation	-0.0301	-0.528	-1.322	-3.403
	[.915]	[.43]	[.006]	[.058]
Number of days extreme precipitation	-0.0731	0.205	0.0941	-0.0468
	[.382]	[.232]	[.467]	[.891]
Fixed Effects:	County Year	County Year	County Year	County Year
Observations	127284	127177	125107	84924

p-values shown in brackets.

Table A2

Population

	(1) PDL(0,29)	(2) ADL(0,29)	(3) ADL(0,9)	(4) ADL(0,3)	(5) ADL(0,1)	(6) ADL(0,0)	(7) PDL(1,29)	(8) PDL(3,29)
Contemporaneous Effects:								
Number of days below 20F	-0.00408	-0.00508	-0.00380	-0.00568	-0.00361	-0.00477	-0.00442	-0.00429
	[0.063]	[0.029]	[0.107]	[0.019]	[0.141]	[0.052]	[0.010]	[0.010]
Number of days between 20 and 50F	0.00188	0.000190	0.00223	0.00225	0.00251	0.00239	0.00139	0.000897
	[0.192]	[0.904]	[0.151]	[0.152]	[0.117]	[0.138]	[0.239]	[0.431]
Number of days between 70 and 80F	0.000289	0.00150	0.000227	-0.000763	-0.00135	-0.000749	0.000758	0.000650
	[0.805]	[0.220]	[0.852]	[0.547]	[0.312]	[0.584]	[0.439]	[0.498]
Number of days temp above 80F	0.00226	0.00275	0.000979	-0.00124	-0.00257	-0.00225	0.00231	0.00190
	[0.266]	[0.160]	[0.624]	[0.574]	[0.265]	[0.339]	[0.148]	[0.229]
Daily Precipitation	-0.0244	-0.0113	-0.0247	-0.0301	-0.0464	-0.0414	-0.0153	-0.0160
	[0.353]	[0.652]	[0.349]	[0.272]	[0.106]	[0.153]	[0.459]	[0.434]
Number of days with extreme precipitation	-0.00420	-0.00790	-0.00515	-0.00356	-0.00273	-0.00328	-0.00458	-0.00375
	[0.513]	[0.215]	[0.439]	[0.594]	[0.689]	[0.631]	[0.423]	[0.501]
Sum of Contemp. & Lagged Effects:								
Number of days below 20F	-0.0923	-0.0853	-0.0394	-0.0347	-0.0144	-0.00477	-0.104	-0.0744
	[0]	[0]	[0]	[0]	[0]	[.052]	[0]	[0]
Number of days between 20 and 50F	-0.0157	-0.00881	-0.00620	-0.00470	0.000100	0.00239	-0.0220	-0.0192
	[.242]	[.504]	[.306]	[.118]	[.962]	[.138]	[.148]	[.087]
Number of days between 70 and 80F	-0.0505	-0.0447	-0.0211	-0.0102	-0.00252	-0.000750	-0.0474	-0.0313
	[0]	[0]	[0]	[.001]	[.202]	[.584]	[0]	[0]
Number of days above 80F	-0.0540	-0.0474	-0.0482	-0.0205	-0.00737	-0.00225	-0.0544	-0.0377
	[0]	[0]	[0]	[0]	[.023]	[.338]	[0]	[0]
Daily Precipitation	-0.0301	-0.0881	0.0116	0.0119	-0.0590	-0.0414	0.0567	0.0694
	[.915]	[.747]	[.923]	[.846]	[.162]	[.152]	[.864]	[.778]
Number of days extreme precipitation	-0.0731	-0.0858	-0.0983	-0.0571	-0.0192	-0.00328	-0.104	-0.0755
	[.382]	[.285]	[0]	[.001]	[.078]	[.631]	[.322]	[.339]
Sum of LDV coefficients							0.296	0.404
							[0]	[0]
Fixed Effects:	County Year	County Year	County Year	County Year	County Year	County Year	County Year	County Year
Observations	127284	127284	127284	127284	127284	127284	127283	127281

p-values shown in brackets.

Table A3

Total Employment

	(1) PDL(0,29)	(2) ADL(0,29)	(3) ADL(0,9)	(4) ADL(0,3)	(5) ADL(0,1)	(6) ADL(0,0)	(7) PDL(1,29)	(8) PDL(3,29)
Contemporaneous Effects:								
Number of days below 20F	-0.0131	-0.00477	-0.0151	-0.0189	-0.0133	-0.0158	-0.0141	-0.0148
	[0.052]	[0.511]	[0.030]	[0.008]	[0.059]	[0.024]	[0.045]	[0.038]
Number of days between 20 and 50F	-0.00272	-0.000993	-0.00434	-0.00538	-0.00307	-0.00357	-0.00319	-0.00327
	[0.475]	[0.816]	[0.273]	[0.179]	[0.442]	[0.364]	[0.426]	[0.424]
Number of days between 70 and 80F	0.00515	0.00168	0.00242	0.00279	0.00209	0.00414	0.00479	0.00465
	[0.161]	[0.641]	[0.516]	[0.459]	[0.591]	[0.289]	[0.209]	[0.229]
Number of days temp above 80F	0.0158	0.0176	0.0169	0.0146	0.0131	0.0139	0.0158	0.0162
	[0.029]	[0.009]	[0.018]	[0.050]	[0.080]	[0.055]	[0.035]	[0.032]
Daily Precipitation	0.0189	-0.0263	0.0386	0.0364	0.0106	0.00780	0.0131	0.00974
	[0.822]	[0.738]	[0.632]	[0.659]	[0.900]	[0.927]	[0.879]	[0.910]
Number of days with extreme precipitation	-0.0244	-0.0181	-0.0333	-0.0315	-0.0273	-0.0273	-0.0251	-0.0250
	[0.256]	[0.355]	[0.112]	[0.143]	[0.209]	[0.210]	[0.255]	[0.261]
Sum of Contemp. & Lagged Effects:								
Number of days below 20F	-0.141	-0.111	-0.0848	-0.0914	-0.0332	-0.0158	-0.142	-0.157
	[.002]	[.013]	[0]	[0]	[0]	[.024]	[.002]	[.001]
Number of days between 20 and 50F	-0.0940	-0.0679	-0.0290	-0.0346	-0.0156	-0.00357	-0.0928	-0.0993
	[.002]	[.024]	[.052]	[0]	[.002]	[.364]	[.002]	[.002]
Number of days between 70 and 80F	-0.0381	-0.0429	0.0139	-0.0140	-0.00839	0.00414	-0.0394	-0.0452
	[.102]	[.064]	[.27]	[.079]	[.121]	[.289]	[.085]	[.067]
Number of days above 80F	-0.0716	-0.0499	-0.00809	-0.0157	-0.00183	0.0139	-0.0718	-0.0801
	[.009]	[.063]	[.605]	[.099]	[.8310]	[.055]	[.008]	[.006]
Daily Precipitation	-0.528	-0.765	0.551	0.0629	0.150	0.00780	-0.523	-0.587
	[.43]	[.225]	[.043]	[.71]	[.217]	[.927]	[.42]	[.4]
Number of days extreme precipitation	0.205	0.176	-0.142	-0.0892	-0.0589	-0.0273	0.200	0.213
	[.232]	[.293]	[.041]	[.055]	[.069]	[.21]	[.232]	[.239]
Sum of LDV coefficients							-0.0872	-0.142
							[0]	[0]
Fixed Effects:	County Year	County Year	County Year	County Year	County Year	County Year	County Year	County Year
Observations	127177	127177	127177	127177	127177	127177	127160	127125

p-values shown in brackets.

Table A4

Wages

	(1) PDL(0,29)	(2) ADL(0,29)	(3) ADL(0,9)	(4) ADL(0,3)	(5) ADL(0,1)	(6) ADL(0,0)	(7) PDL(1,29)	(8) PDL(3,29)
Contemporaneous Effects:								
Number of days below 20F	0.00782	0.00402	0.00779	0.00899	0.00910	0.00902	0.0109	0.0124
	[0.111]	[0.453]	[0.126]	[0.080]	[0.068]	[0.068]	[0.029]	[0.014]
Number of days between 20 and 50F	-0.00116	-0.00600	-0.000943	0.000216	0.0000138	0.000340	-0.000303	0.000583
	[0.695]	[0.059]	[0.756]	[0.944]	[0.996]	[0.909]	[0.920]	[0.846]
Number of days between 70 and 80F	-0.0104	-0.0119	-0.00912	-0.0109	-0.0109	-0.0109	-0.00989	-0.0103
	[0.000]	[0.000]	[0.001]	[0.000]	[0.000]	[0.000]	[0.001]	[0.001]
Number of days temp above 80F	-0.00632	-0.0139	-0.00943	-0.00867	-0.00903	-0.00918	-0.00446	-0.00442
	[0.110]	[0.001]	[0.016]	[0.026]	[0.019]	[0.015]	[0.259]	[0.267]
Daily Precipitation	-0.0252	-0.0666	-0.0425	-0.0392	-0.0435	-0.0376	-0.0213	-0.0367
	[0.708]	[0.288]	[0.518]	[0.560]	[0.513]	[0.573]	[0.751]	[0.582]
Number of days with extreme precipitation	0.0212	0.0226	0.0245	0.0236	0.0226	0.0210	0.0225	0.0237
	[0.274]	[0.212]	[0.200]	[0.225]	[0.246]	[0.283]	[0.250]	[0.223]
Sum of Contemp. & Lagged Effects:								
Number of days below 20F	0.0264	0.0331	0.00334	0.0117	0.00856	0.00902	0.0223	0.0249
	[.438]	[.318]	[.8220]	[.283]	[.208]	[.067]	[.475]	[.524]
Number of days between 20 and 50F	0.0282	0.0249	-0.00927	0.00380	0.000800	0.000340	0.0244	0.0285
	[.146]	[.18]	[.314]	[.598]	[.855]	[.909]	[.172]	[.204]
Number of days between 70 and 80F	-0.0419	-0.0435	-0.0243	-0.0117	-0.00789	-0.0109	-0.0408	-0.0502
	[.01]	[.005]	[.009]	[.058]	[.059]	[0]	[.006]	[.008]
Number of days above 80F	-0.0497	-0.0589	-0.0485	-0.0182	-0.0112	-0.00918	-0.0471	-0.0574
	[.004]	[0]	[0]	[.006]	[.022]	[.015]	[.003]	[.004]
Daily Precipitation	-1.322	-1.429	-0.512	-0.248	-0.155	-0.0376	-1.228	-1.556
	[.006]	[.001]	[.019]	[.064]	[.095]	[.5730]	[.006]	[.004]
Number of days extreme precipitation	0.0941	0.0887	0.0875	0.0485	0.0118	0.0210	0.0897	0.119
	[.467]	[.472]	[.1]	[.155]	[.652]	[.283]	[.46]	[.433]
Sum of LDV coefficients							-0.172	-0.372
							[0]	[0]
Fixed Effects:	County Year	County Year	County Year	County Year	County Year	County Year	County Year	County Year
Observations	125107	125107	125107	125107	125107	125107	125088	125052

p-values shown in brackets.

Table A5

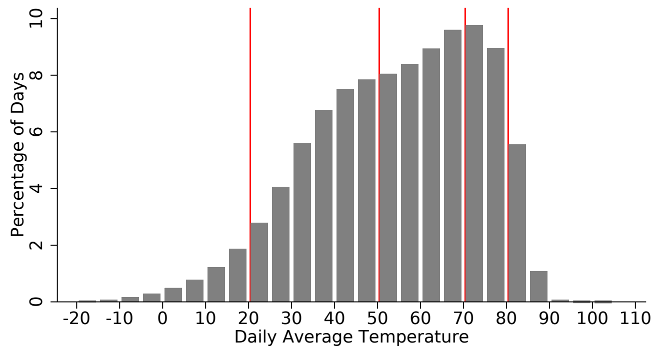
House Prices

	(1) PDL(0,29)	(2) ADL(0,29)	(3) ADL(0,9)	(4) ADL(0,3)	(5) ADL(0,1)	(6) ADL(0,0)	(7) PDL(1,29)	(8) PDL(3,29)
Contemporaneous Effects:								
Number of days below 20F	-0.00500	0.00571	0.000883	-0.00395	0.00188	0.00108	-0.00875	-0.00868
	[0.772]	[0.712]	[0.961]	[0.819]	[0.914]	[0.951]	[0.554]	[0.554]
Number of days between 20 and 50F	-0.0162	-0.00224	-0.0100	-0.0138	-0.0120	-0.0146	-0.0171	-0.0180
	[0.184]	[0.818]	[0.391]	[0.257]	[0.332]	[0.232]	[0.101]	[0.079]
Number of days between 70 and 80F	-0.0158	-0.0126	-0.0150	-0.0166	-0.0179	-0.0158	-0.0138	-0.0127
	[0.155]	[0.148]	[0.180]	[0.144]	[0.120]	[0.167]	[0.145]	[0.175]
Number of days temp above 80F	0.00337	0.00623	0.00856	0.00864	0.00559	0.00803	-0.000102	-0.000835
	[0.824]	[0.595]	[0.558]	[0.558]	[0.706]	[0.581]	[0.994]	[0.949]
Daily Precipitation	0.0377	-0.0721	-0.0174	0.00420	-0.0155	-0.0161	0.0485	0.0424
	[0.839]	[0.642]	[0.921]	[0.982]	[0.936]	[0.933]	[0.767]	[0.795]
Number of days with extreme precipitation	0.000995	-0.0247	-0.00441	0.0181	0.0176	0.0192	0.000745	0.00331
	[0.982]	[0.518]	[0.916]	[0.684]	[0.693]	[0.667]	[0.985]	[0.934]
Sum of Contemp. & Lagged Effects:								
Number of days below 20F	0.00791	0.130	-0.0211	-0.0925	-0.0165	0.00108	0.00458	-0.00195
	[.9360]	[.126]	[.754]	[.005]	[.454]	[.9510]	[.966]	[.984]
Number of days between 20 and 50F	-0.0187	0.0675	-0.0505	-0.0599	-0.0282	-0.0146	-0.0213	-0.0187
	[.783]	[.227]	[.195]	[.004]	[.077]	[.232]	[.775]	[.782]
Number of days between 70 and 80F	-0.131	-0.129	-0.0451	-0.0652	-0.0298	-0.0158	-0.123	-0.100
	[.007]	[.003]	[.157]	[.005]	[.059]	[.167]	[.019]	[.04]
Number of days above 80F	-0.0795	-0.0509	-0.0308	-0.0178	0.0108	0.00803	-0.0733	-0.0585
	[.159]	[.341]	[.35]	[.463]	[.5740]	[.581]	[.234]	[.294]
Daily Precipitation	-3.403	-4.436	0.465	-0.298	-0.0972	-0.0161	-3.683	-3.357
	[.058]	[.005]	[.469]	[.476]	[.712]	[.9330]	[.064]	[.073]
Number of days extreme precipitation	-0.0468	-0.164	-0.0302	0.0416	0.0288	0.0192	-0.0117	0.0245
	[.891]	[.589]	[.843]	[.665]	[.648]	[.667]	[.975]	[.9410]
Sum of LDV coefficients							0.203	0.264
							[0]	[0]
Fixed Effects:	County Year	County Year	County Year	County Year	County Year	County Year	County Year	County Year
Observations	84924	84924	84924	84924	84924	84924	83867	81792

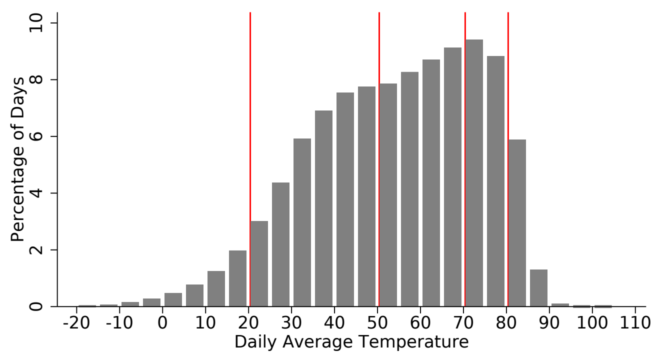
p-values shown in brackets.

Figure A1: Mean County Distribution of Daily Average Temperature

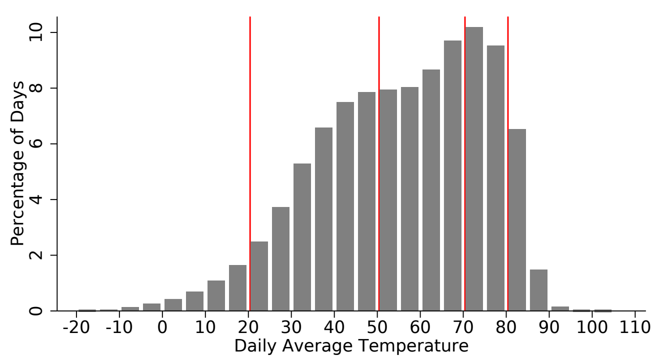
(a) Full Sample, 1951-2020



(b) 1951-1960



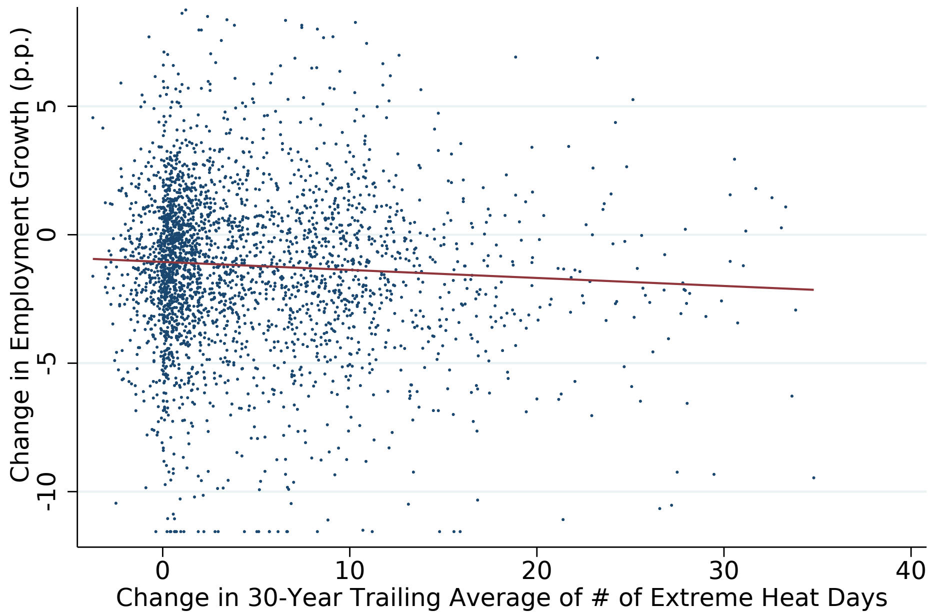
(c) 2011-2020



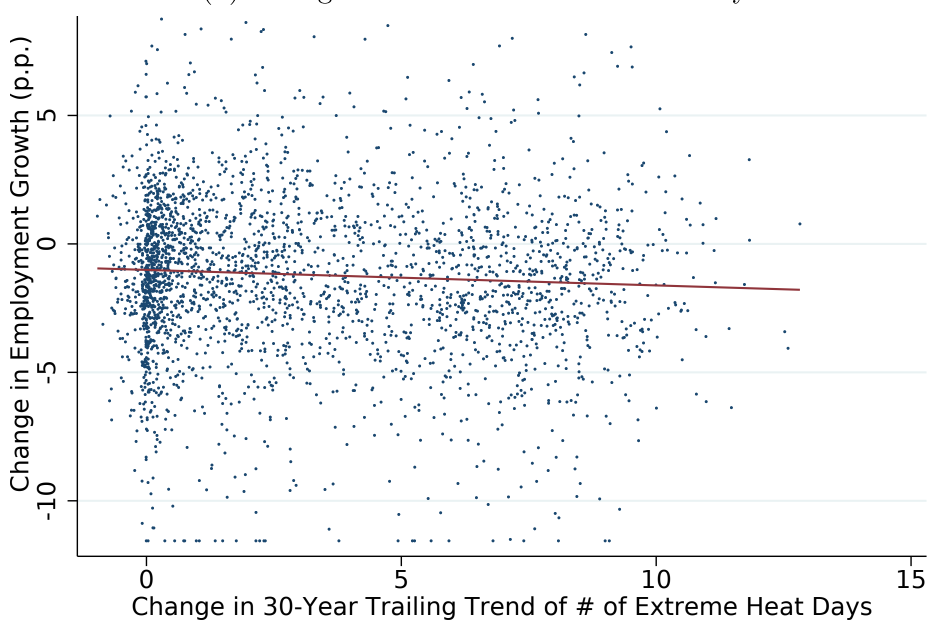
Notes: Each panel shows a histogram of the percentage of days in the indicated time period with a daily average temperature in each 5-degree bin, averaged over all U.S. counties. Vertical red lines are shown at 20, 50, 70, and 80 degrees. The five temperature ranges cut by these four values correspond to the temperature range frequency bins used in our regression analyses.

Figure A2: Cross-County Relationship between Change in Employment Growth and Change in Level or Trend of Extreme Heat Days
1980 to 2020

(a) Change in *Level* of Extreme Heat Days



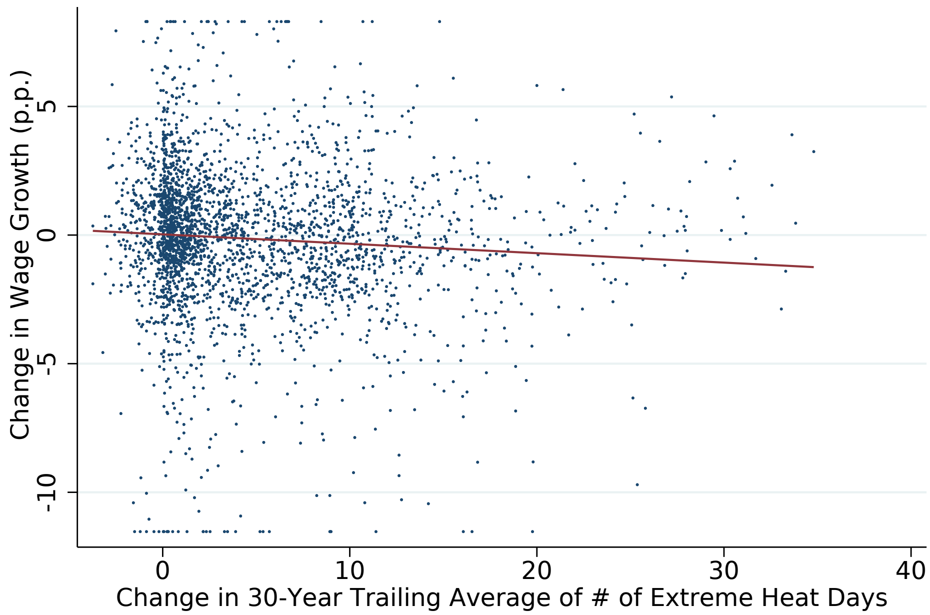
(b) Change in *Trend* of Extreme Heat Days



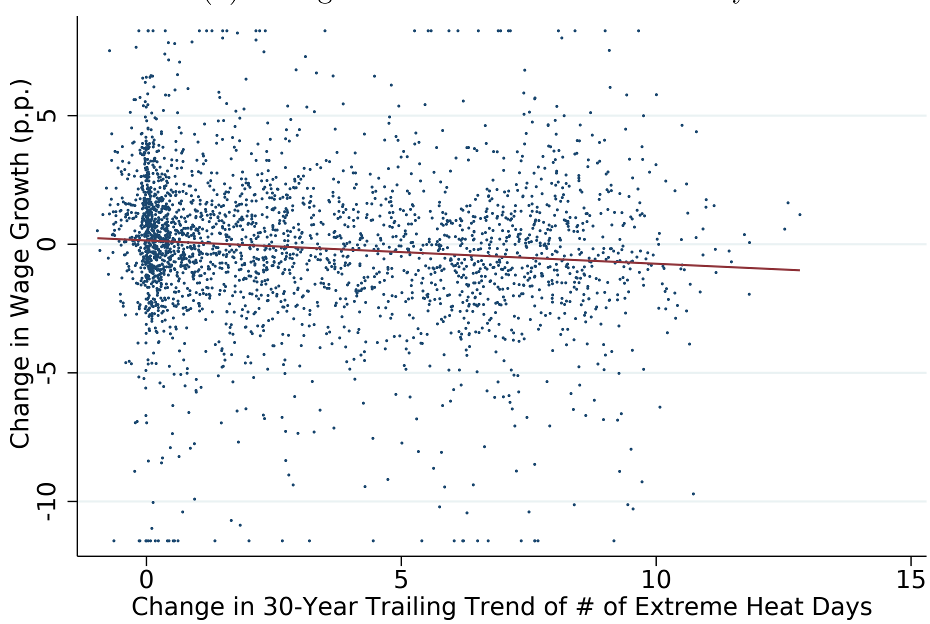
Notes: Each panel displays a scatter plot, where each dot represents a single county. In both panels, the y-axis values are the change (in percentage points) in the county's employment growth rate over the period 1980 to 2020. To reduce noise stemming from idiosyncratic transitory shocks to employment growth at these endpoints, employment growth in 1980 and 2020 is measured using a 10-year trailing average and winsorized at 1st and 99th percentiles. In panel A, the x-axis values are the 1980 to 2020 change in the 30-year trailing *average* of the number of extreme heat days in the county (i.e., the average annual number of extreme heat days over the period 1991-2020 minus that over the period 1951-1980). In panel B, the x-axis values are the 1980 to 2020 change in the 30-year trailing *trend* of the number of extreme heat days in the county (i.e., the average annual change in the number of extreme heat days over the period 1991-2020 minus that over the period 1951-1980). The red line in each panel is a linear OLS regression fit line.

Figure A3: Cross-County Relationship between Change in Wage Growth and Change in Level or Trend of Extreme Heat Days
1980 to 2020

(a) Change in *Level* of Extreme Heat Days



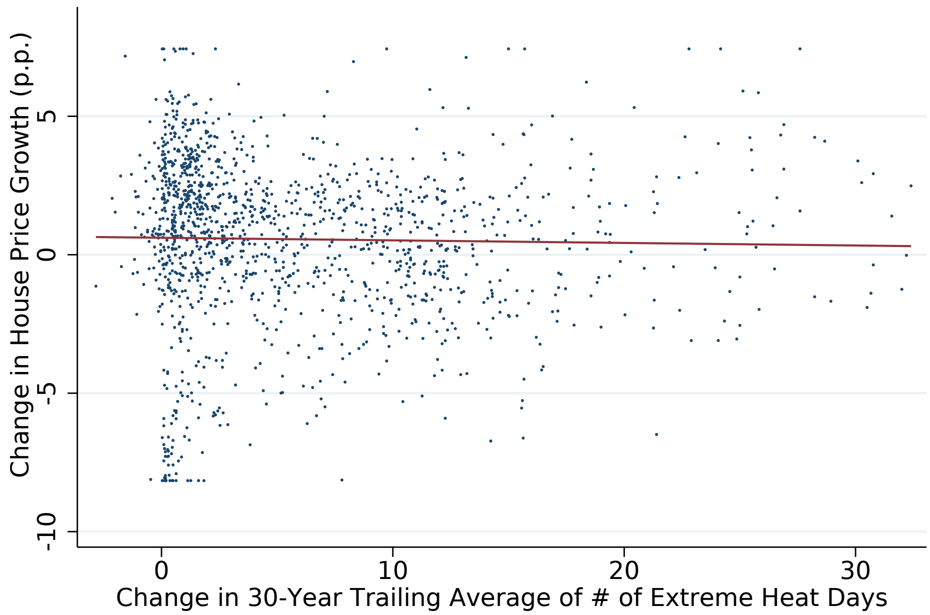
(b) Change in *Trend* of Extreme Heat Days



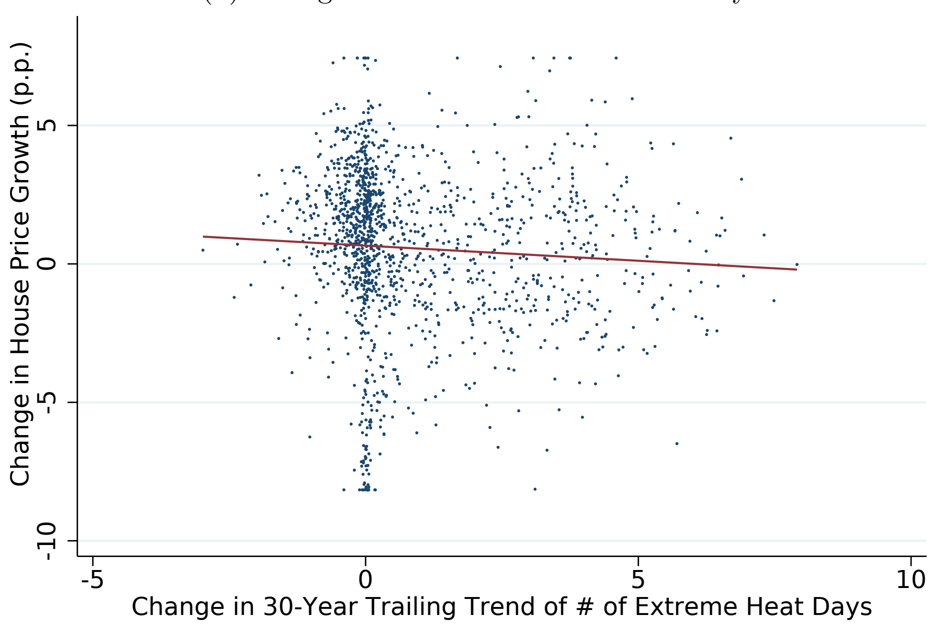
Notes: Each panel displays a scatter plot, where each dot represents a single county. In both panels, the y-axis values are the change (in percentage points) in the county's wage growth rate over the period 1980 to 2020. To reduce noise stemming from idiosyncratic transitory shocks to wage growth at these endpoints, wage growth in 1980 and 2020 is measured using a 10-year trailing average and winsorized at 1st and 99th percentiles. In panel A, the x-axis values are the 1980 to 2020 change in the 30-year trailing *average* of the number of extreme heat days in the county (i.e., the average annual number of extreme heat days over the period 1991-2020 minus that over the period 1951-1980). In panel B, the x-axis values are the 1980 to 2020 change in the 30-year trailing *trend* of the number of extreme heat days in the county (i.e., the average annual change in the number of extreme heat days over the period 1991-2020 minus that over the period 1951-1980). The red line in each panel is a linear OLS regression fit line.

Figure A4: Cross-County Relationship between Change in House Price Growth and Change in Level or Trend of Extreme Heat Days 1980 to 2020

(a) Change in *Level* of Extreme Heat Days



(b) Change in *Trend* of Extreme Heat Days

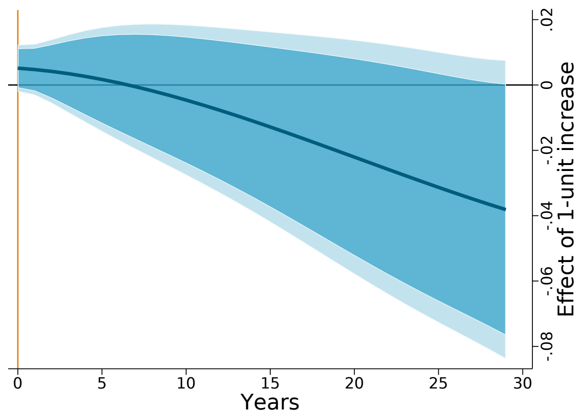


Notes: Each panel displays a scatter plot, where each dot represents a single county. In both panels, the y-axis values are the change (in percentage points) in the county's house price growth rate over the period 1980 to 2020. To reduce noise stemming from idiosyncratic transitory shocks to house price growth at these endpoints, house price growth in 1980 and 2020 is measured using a 10-year trailing average and winsorized at 1st and 99th percentiles. In panel A, the x-axis values are the 1980 to 2020 change in the 30-year trailing *average* of the number of extreme heat days in the county (i.e., the average annual number of extreme heat days over the period 1991-2020 minus that over the period 1951-1980). In panel B, the x-axis values are the 1980 to 2020 change in the 30-year trailing *trend* of the number of extreme heat days in the county (i.e., the average annual change in the number of extreme heat days over the period 1991-2020 minus that over the period 1951-1980). The red line in each panel is a linear OLS regression fit line.

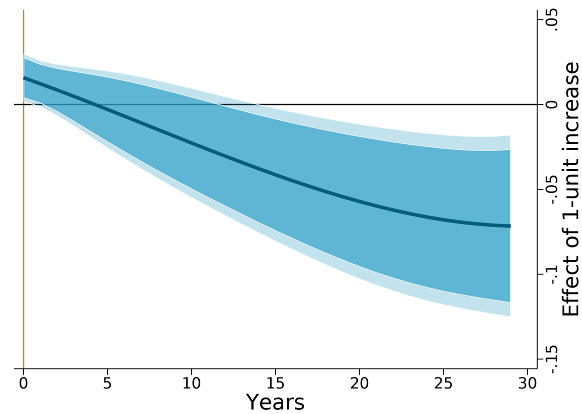
Figure A5: Impulse Response of Employment to Weather

Third-Order Polynomial Distributed Lag Model

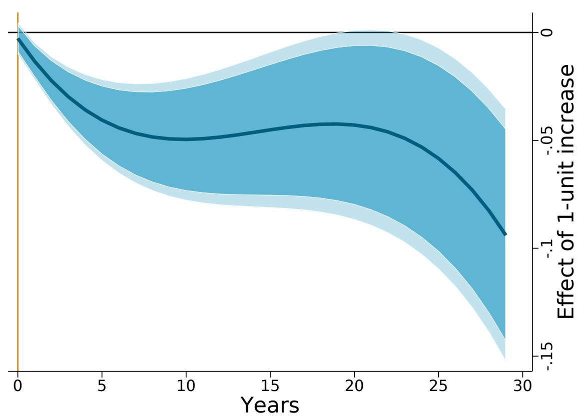
(a) Heat (Days 70 to 80°F (21.1-26.7°C))



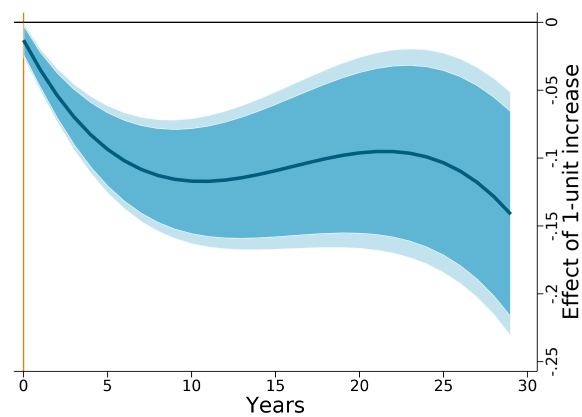
(b) Extreme Heat (Days above 80°F (26.7°C))



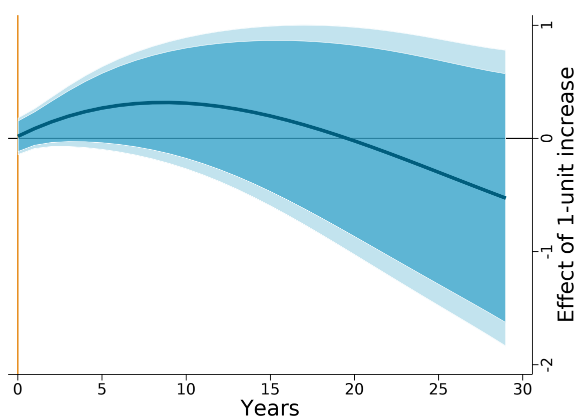
(c) Cold (Days 20 to 50°F (−6.7-10°C))



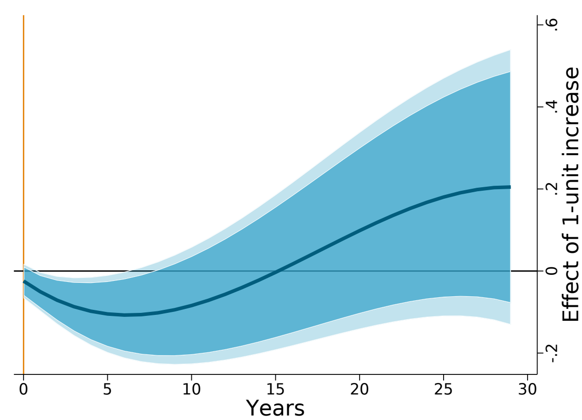
(d) Extreme Cold (Days below 20°F (−6.7°C))



(e) Precipitation



(f) Extreme Precipitation

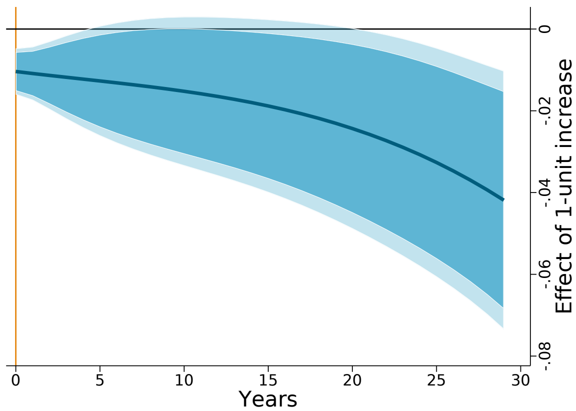


Notes: These plots show the estimated impulse response function of the indicated weather variable for the indicated outcome. The underlying regression includes county and year fixed effects. Standard errors are two-way clustered by county and by year. The inner shaded region shows the 90 percent confidence interval, and the outer lighter shaded region shows the 95 percent confidence intervals.

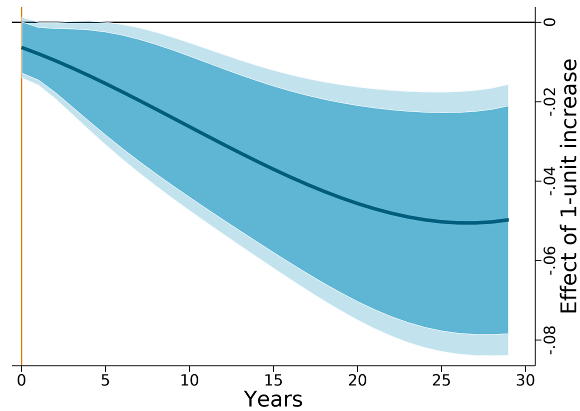
Figure A6: Impulse Response of Wages to Weather

Third-Order Polynomial Distributed Lag Model

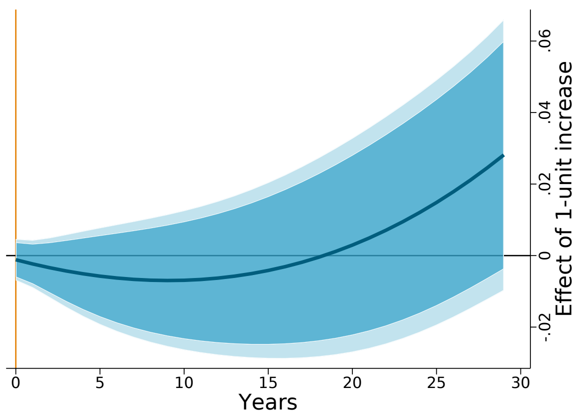
(a) Heat (Days 70 to 80°F (21.1-26.7°C))



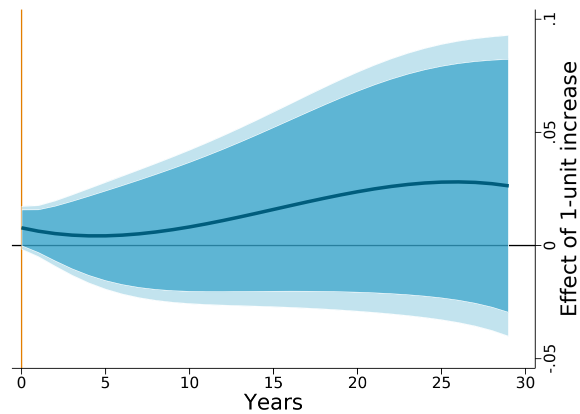
(b) Extreme Heat (Days above 80°F (26.7°C))



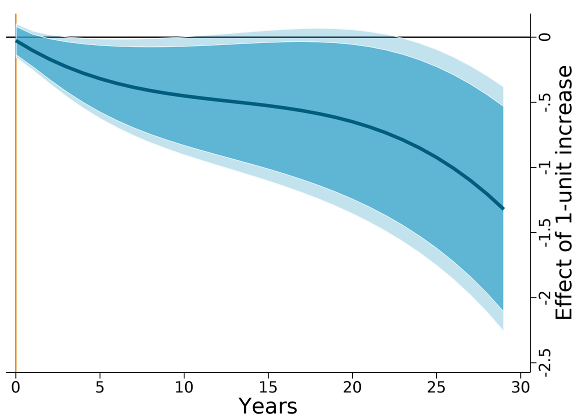
(c) Cold (Days 20 to 50°F (−6.7-10°C))



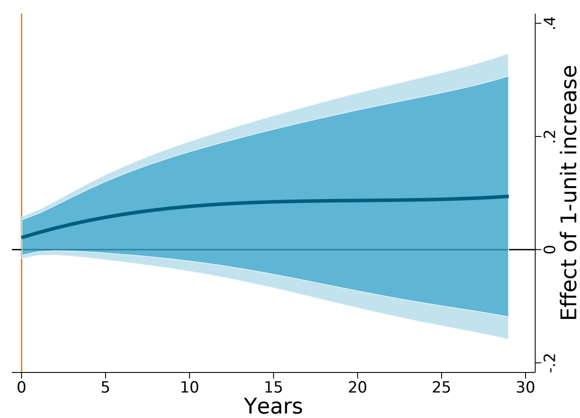
(d) Extreme Cold (Days below 20°F (−6.7°C))



(e) Precipitation



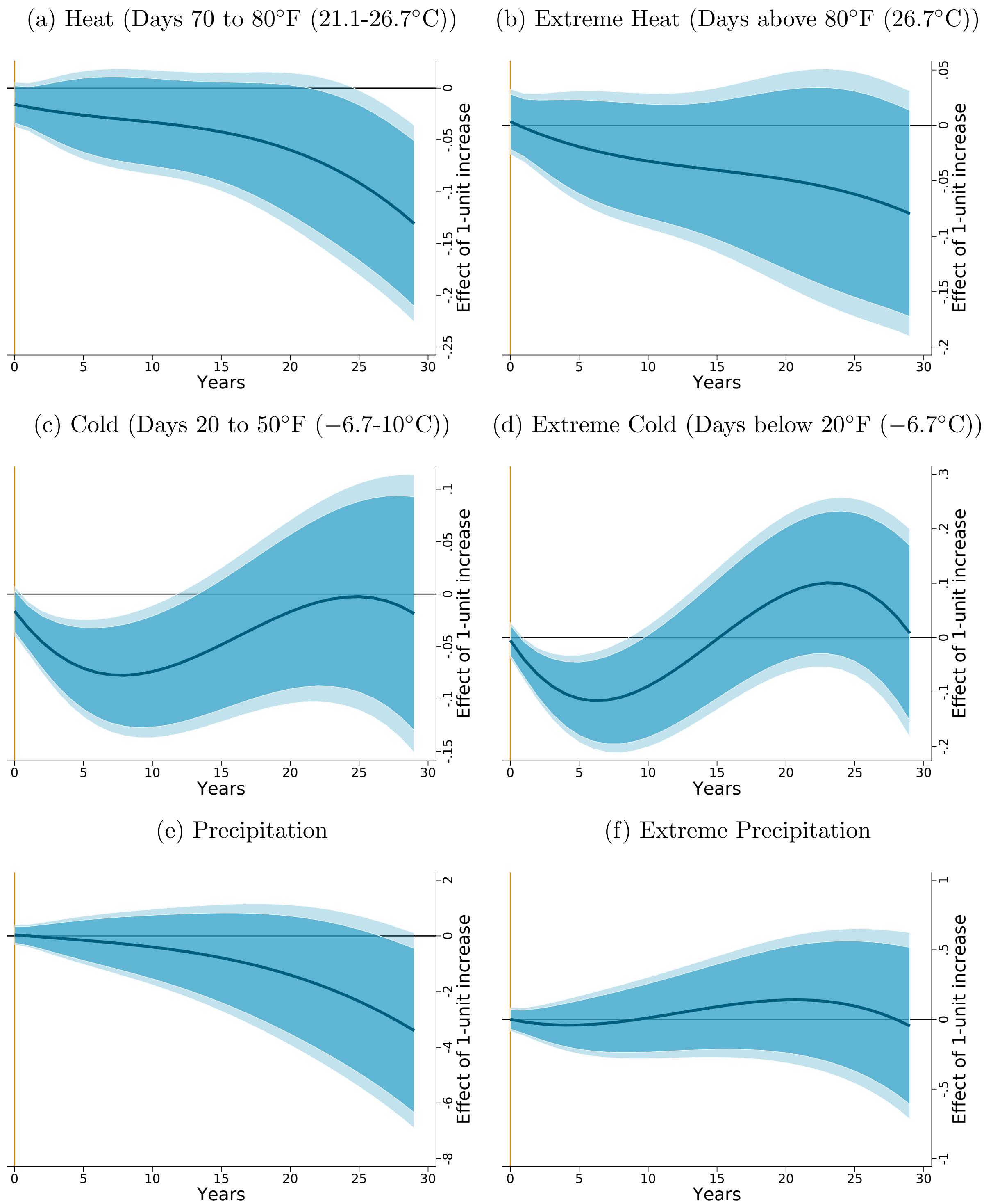
(f) Extreme Precipitation



Notes: These plots show the estimated impulse response function of the indicated weather variable for the indicated outcome. The underlying regression includes county and year fixed effects. Standard errors are two-way clustered by county and by year. The inner shaded region shows the 90 percent confidence interval, and the outer lighter shaded region shows the 95 percent confidence intervals.

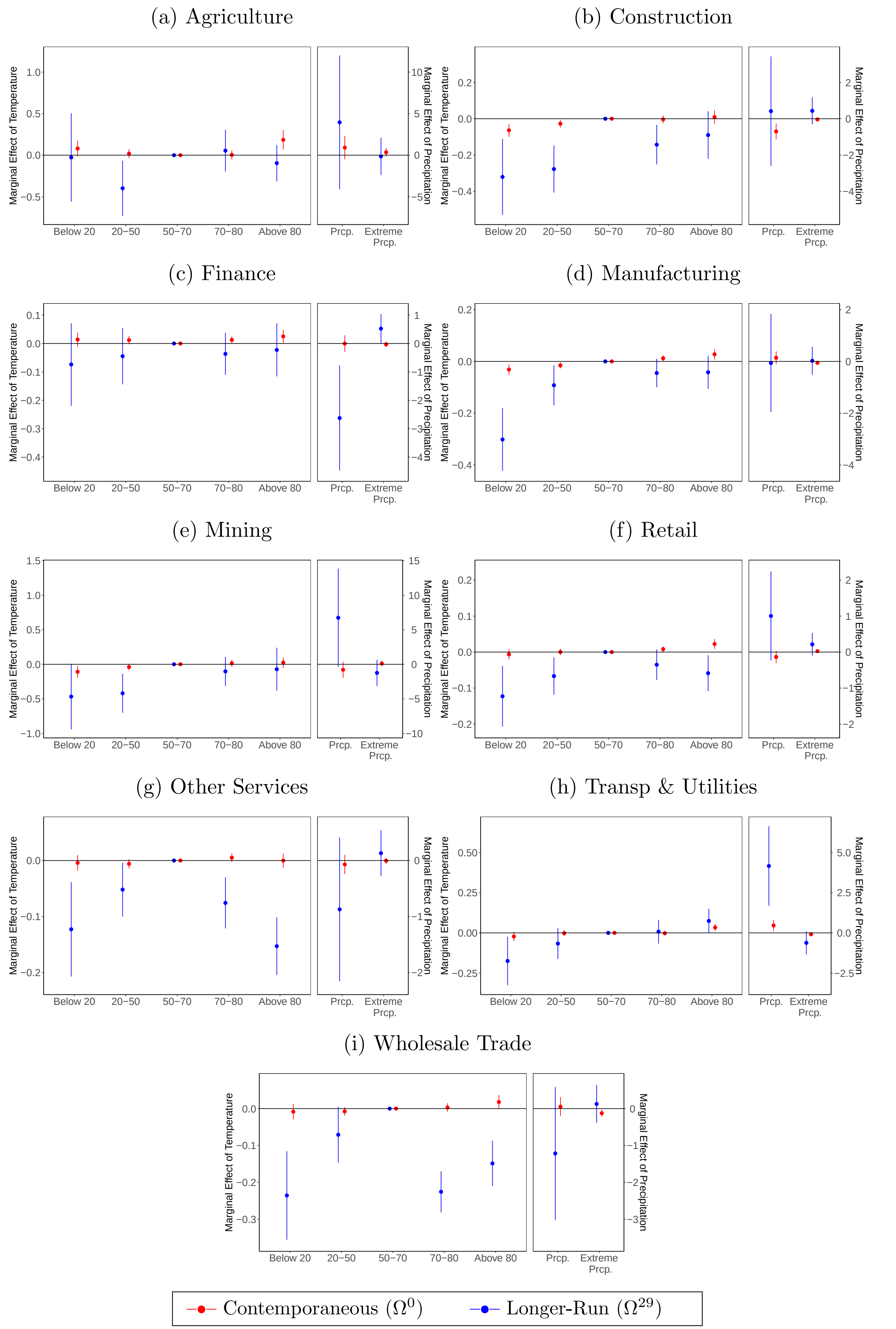
Figure A7: Impulse Response of House Prices to Weather

Third-Order Polynomial Distributed Lag Model



Notes: These plots show the estimated impulse response function of the indicated weather variable for the indicated outcome. The underlying regression includes county and year fixed effects. Standard errors are two-way clustered by county and by year. The inner shaded region shows the 90 percent confidence interval, and the outer lighter shaded region shows the 95 percent confidence intervals.

Figure A8: Contemporaneous and Longer-Run Effects of Weather on Sectoral Employment

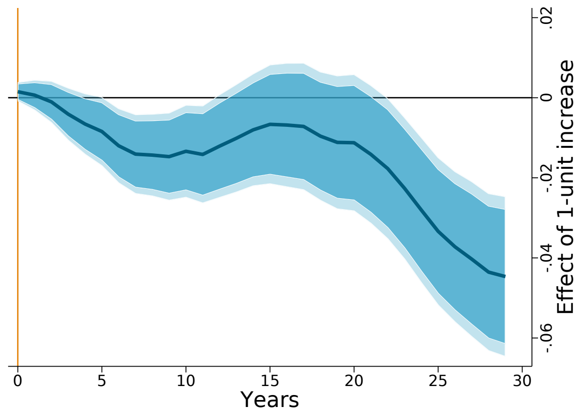


Notes: See notes for Figure 5.

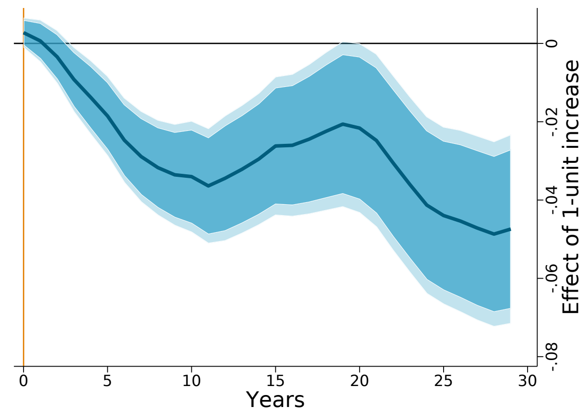
Figure A9: Cumulative Impulse Response of Population to Weather

Unrestricted Distributed Lag Model (29 lags)

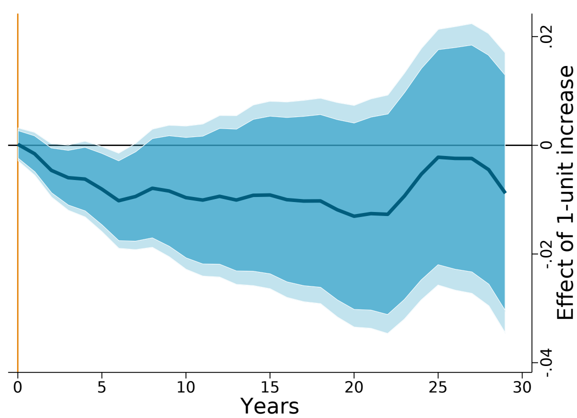
(a) Heat (Days 70 to 80°F (21.1-26.7°C))



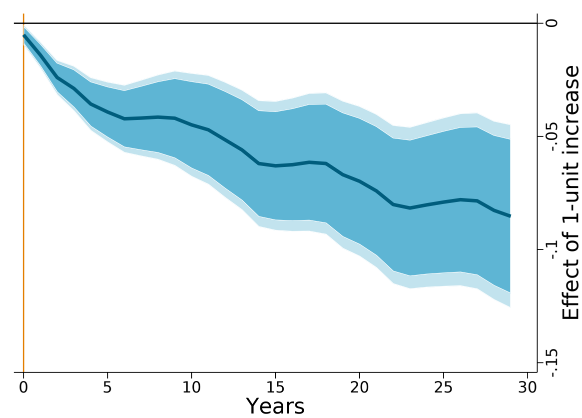
(b) Extreme Heat (Days above 80°F (26.7°C))



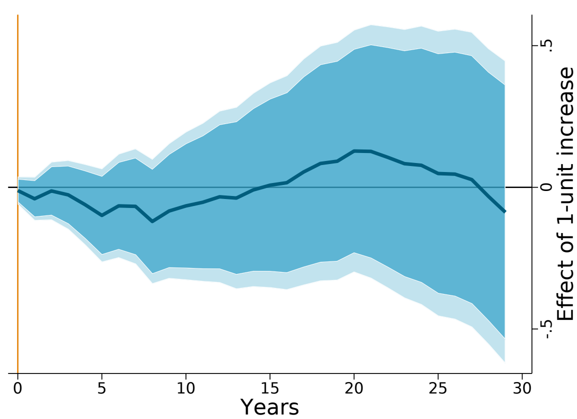
(c) Cold (Days 20 to 50°F (−6.7-10°C))



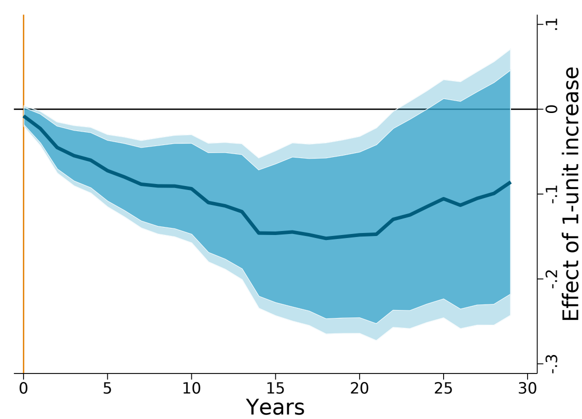
(d) Extreme Cold (Days below 20°F (−6.7°C))



(e) Precipitation



(f) Extreme Precipitation

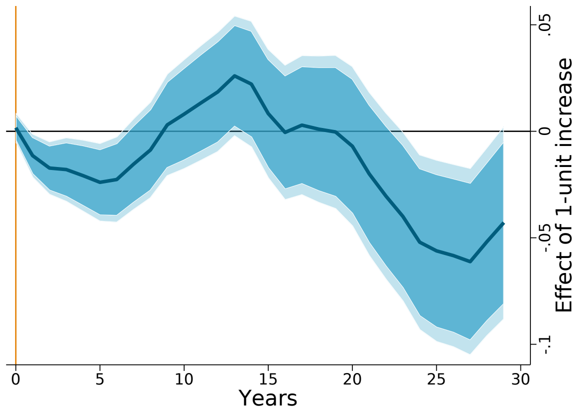


Notes: These plots show the estimated cumulative impulse response function of the indicated weather variable for the indicated outcome. The underlying regression includes county and year fixed effects. Standard errors are two-way clustered by county and by year. The inner shaded region shows the 90 percent confidence interval, and the outer lighter shaded region shows the 95 percent confidence intervals.

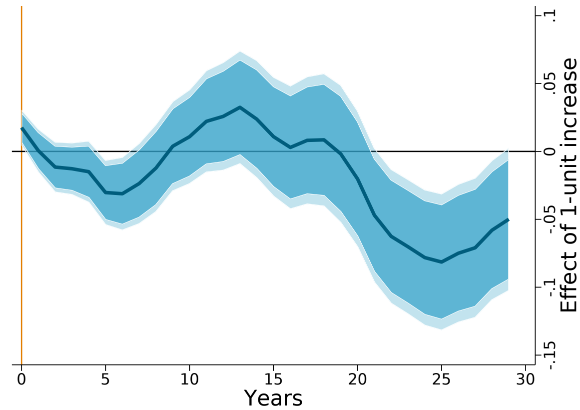
Figure A10: Cumulative Impulse Response of Employment to Weather

Unrestricted Distributed Lag Model (29 lags)

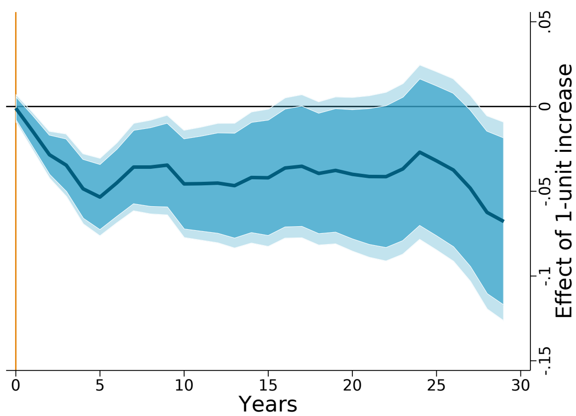
(a) Heat (Days 70 to 80°F (21.1-26.7°C))



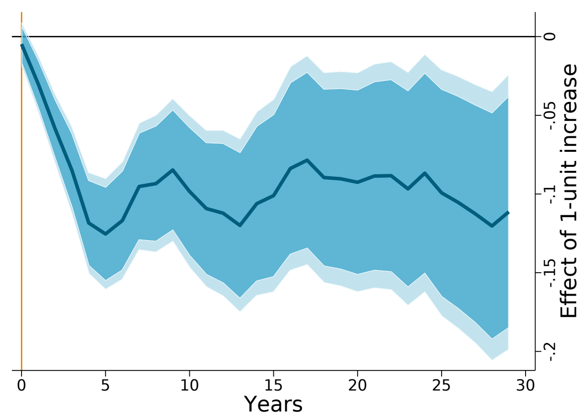
(b) Extreme Heat (Days above 80°F (26.7°C))



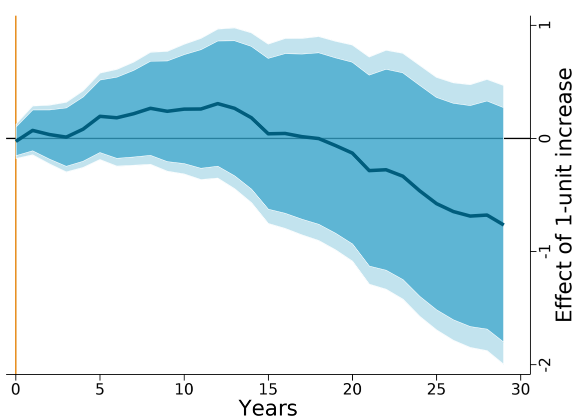
(c) Cold (Days 20 to 50°F (-6.7-10°C))



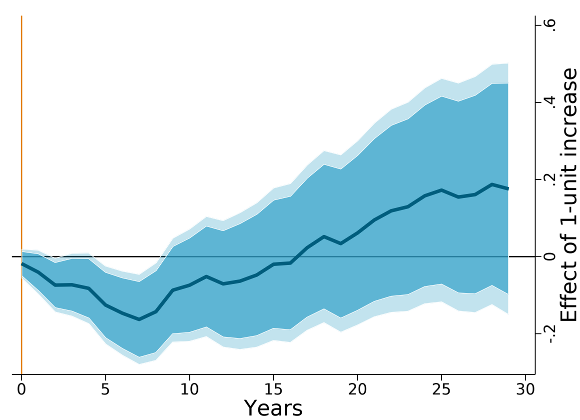
(d) Extreme Cold (Days below 20°F (-6.7°C))



(e) Precipitation



(f) Extreme Precipitation

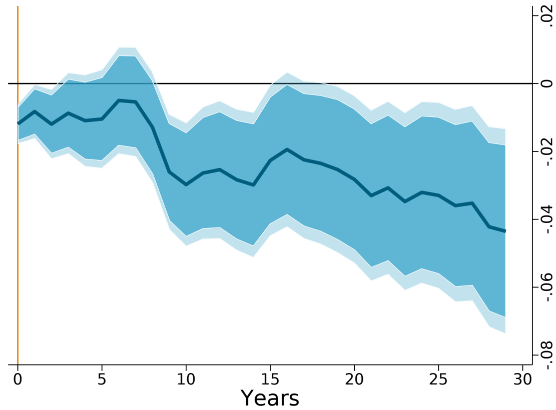


Notes: These plots show the estimated cumulative impulse response function of the indicated weather variable for the indicated outcome. The underlying regression includes county and year fixed effects. Standard errors are two-way clustered by county and by year. The inner shaded region shows the 90 percent confidence interval, and the outer lighter shaded region shows the 95 percent confidence intervals.

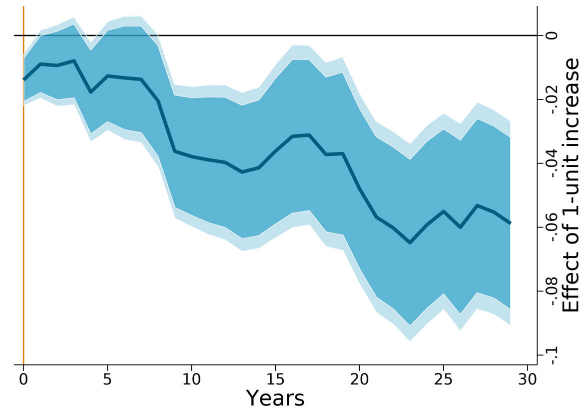
Figure A11: Cumulative Impulse Response of Wages to Weather

Unrestricted Distributed Lag Model (29 lags)

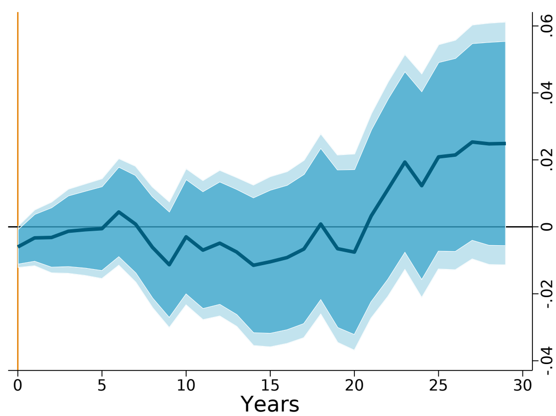
(a) Heat (Days 70 to 80°F (21.1-26.7°C))



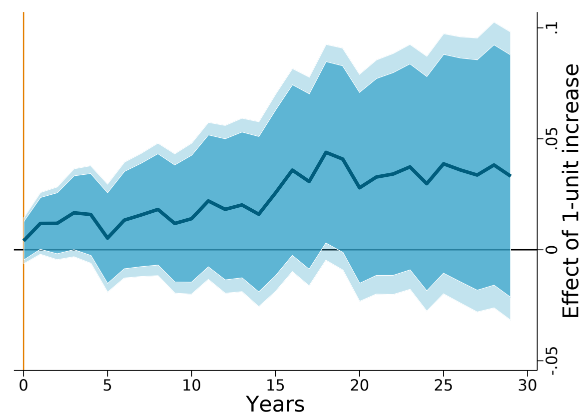
(b) Extreme Heat (Days above 80°F (26.7°C))



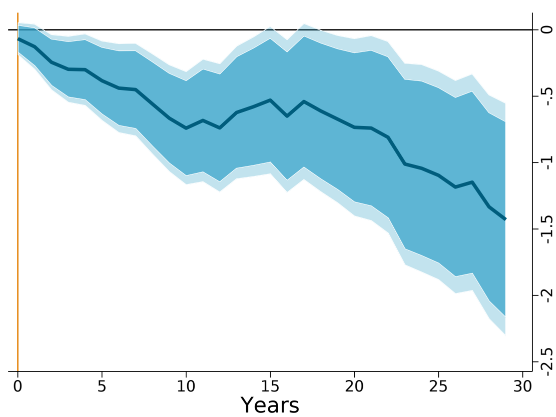
(c) Cold (Days 20 to 50°F (−6.7-10°C))



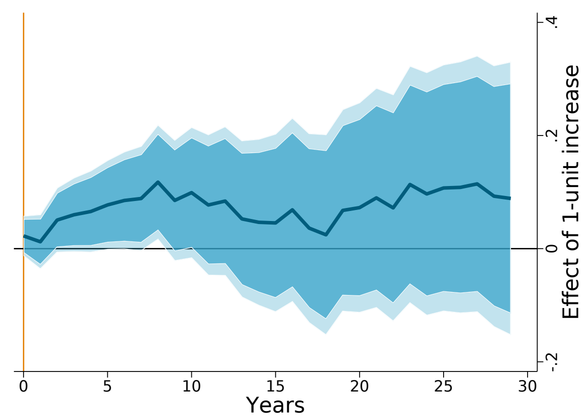
(d) Extreme Cold (Days below 20°F (−6.7°C))



(e) Precipitation



(f) Extreme Precipitation

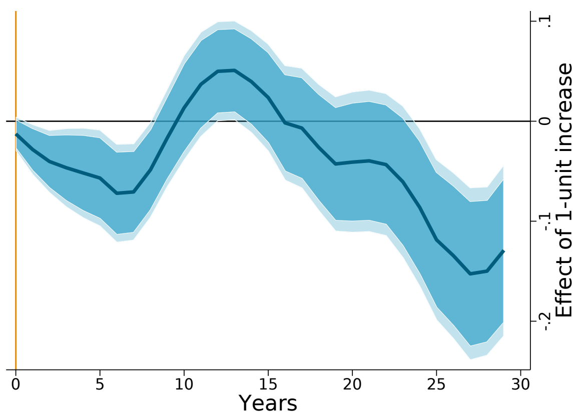


Notes: These plots show the estimated cumulative impulse response function of the indicated weather variable for the indicated outcome. The underlying regression includes county and year fixed effects. Standard errors are two-way clustered by county and by year. The inner shaded region shows the 90 percent confidence interval, and the outer lighter shaded region shows the 95 percent confidence intervals.

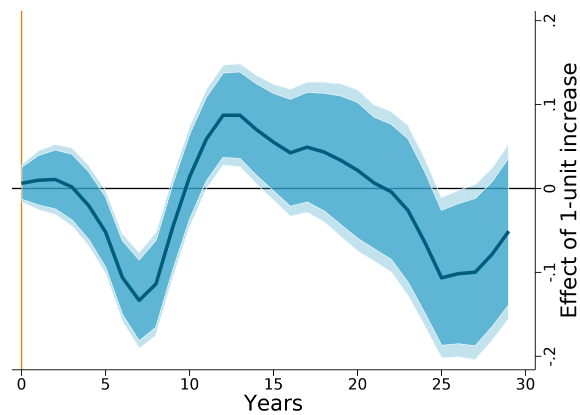
Figure A12: Cumulative Impulse Response of House Prices to Weather

Unrestricted Distributed Lag Model (29 lags)

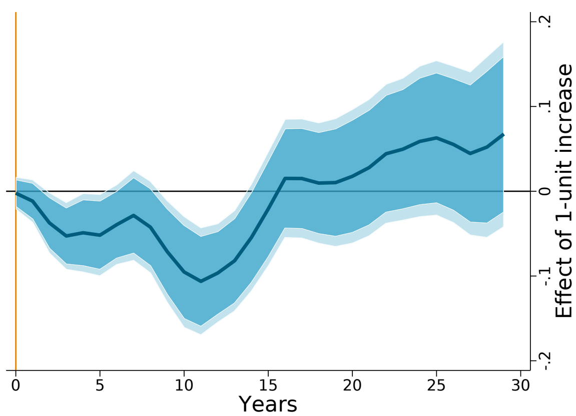
(a) Heat (Days 70 to 80°F (21.1-26.7°C))



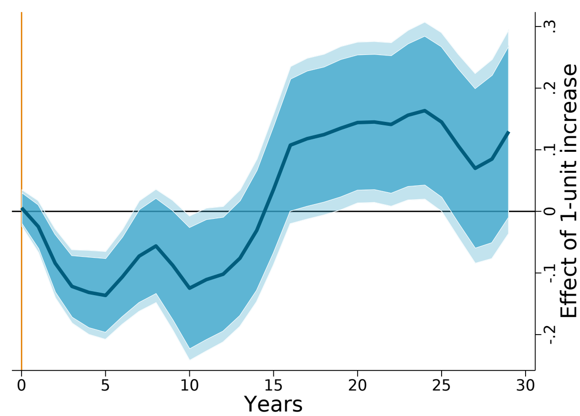
(b) Extreme Heat (Days above 80°F (26.7°C))



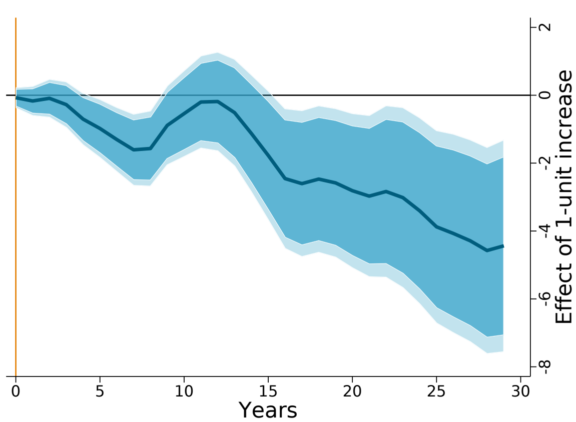
(c) Cold (Days 20 to 50°F (−6.7-10°C))



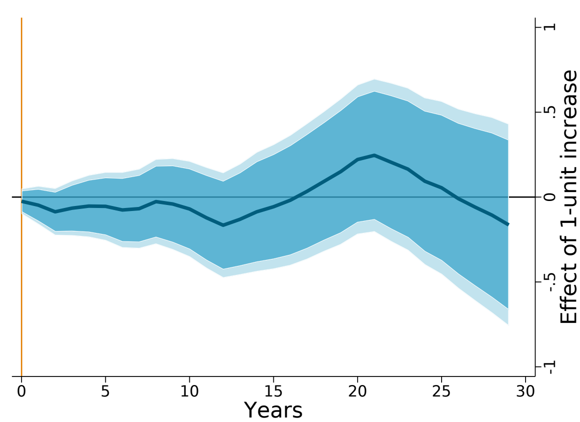
(d) Extreme Cold (Days below 20°F (−6.7°C))



(e) Precipitation



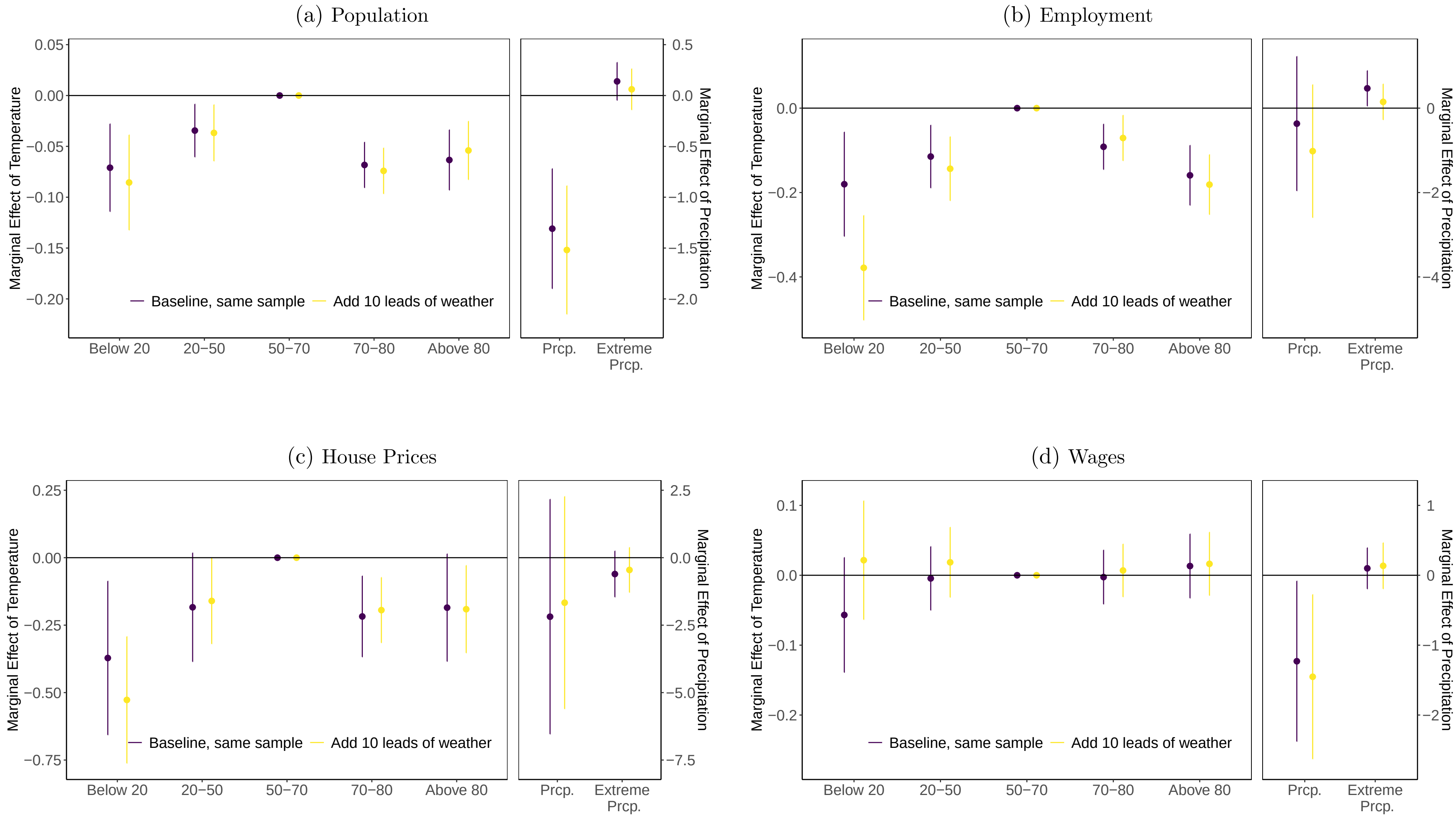
(f) Extreme Precipitation



Notes: These plots show the estimated cumulative impulse response function of the indicated weather variable for the indicated outcome. The underlying regression includes county and year fixed effects. Standard errors are two-way clustered by county and by year. The inner shaded region shows the 90 percent confidence interval, and the outer lighter shaded region shows the 95 percent confidence intervals.

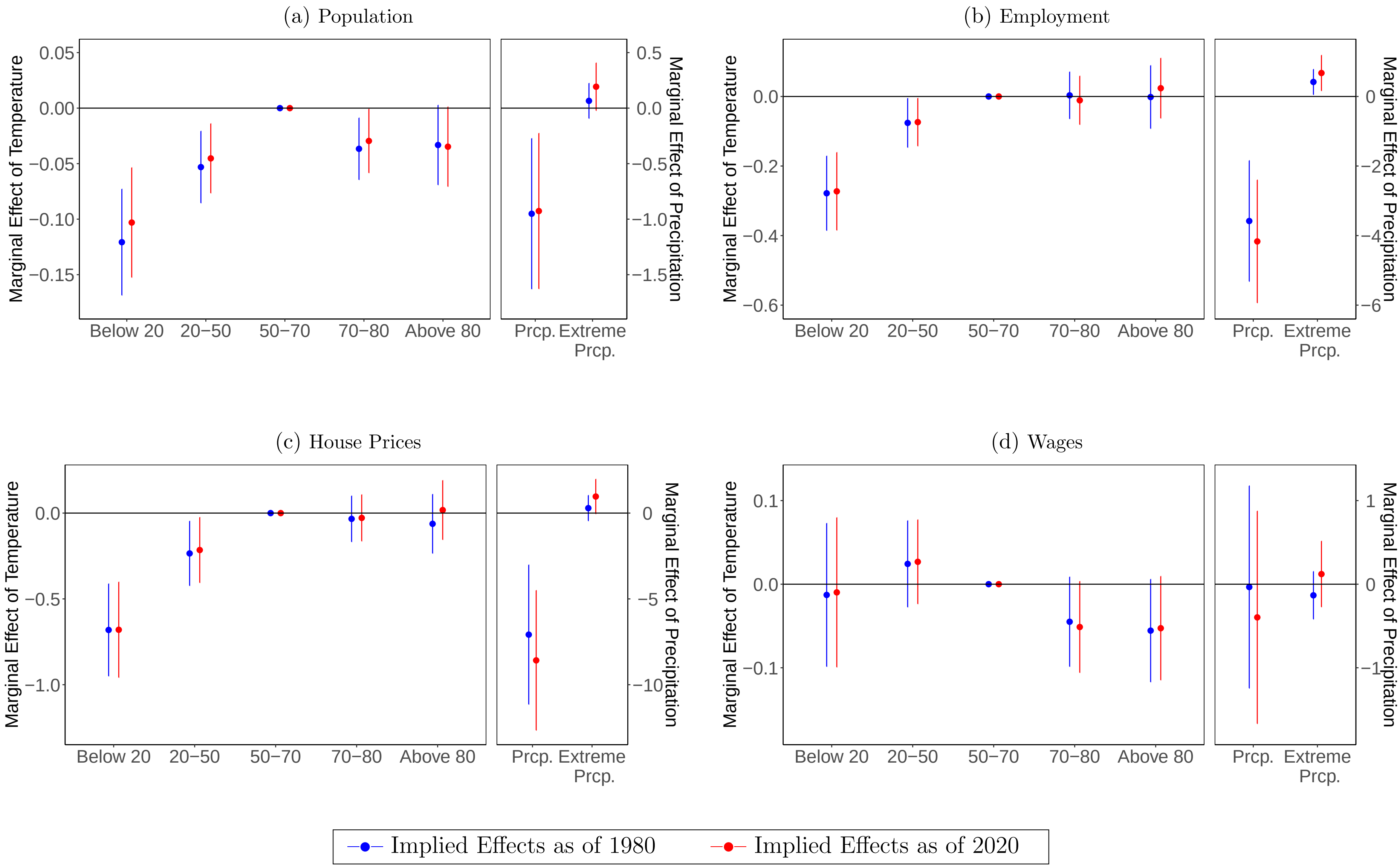
Figure A13: Longer-Run Marginal Effects of Weather

Assessing the Role of Pre-Trends



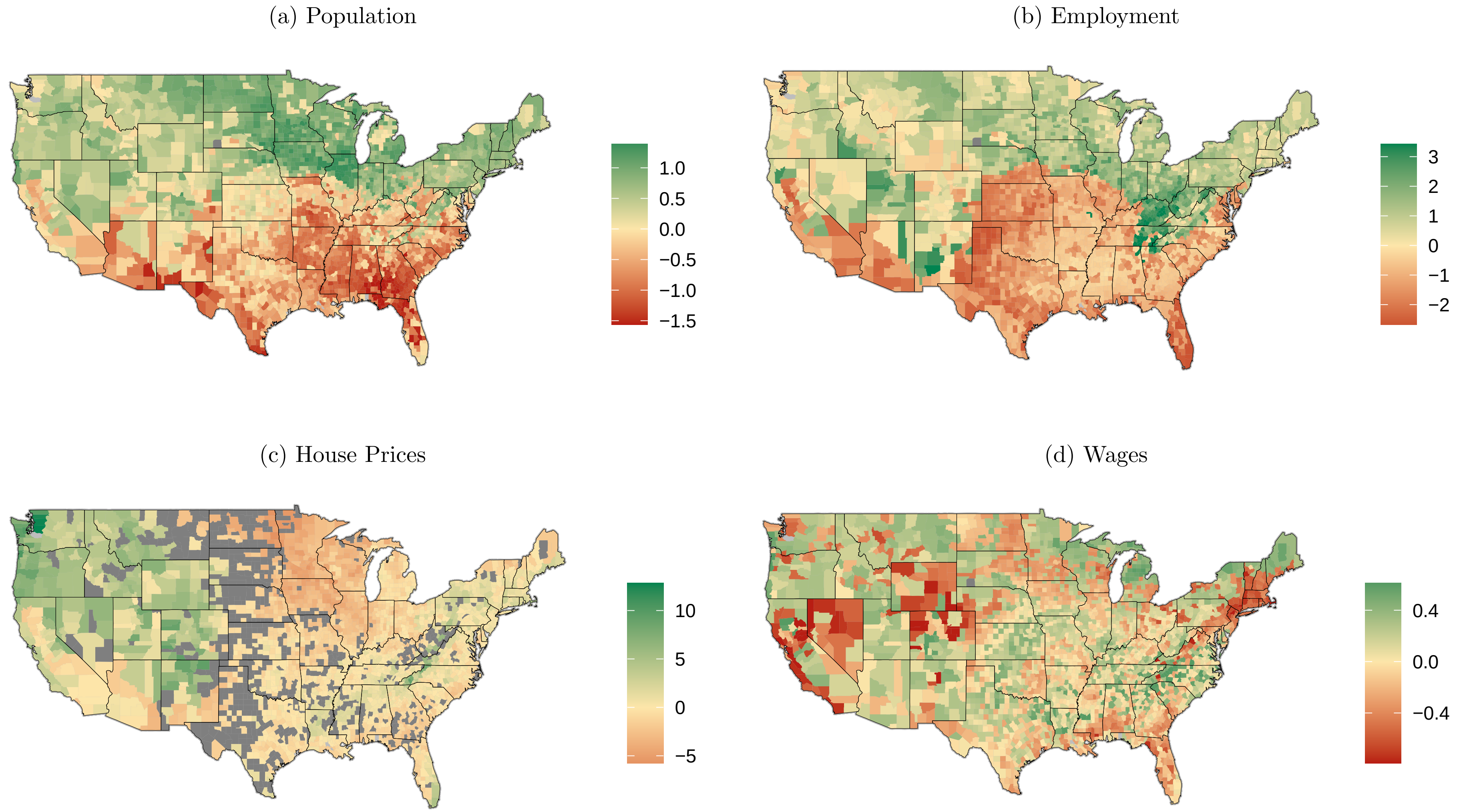
Notes: Each plot shows the estimated longer-run marginal weather effects based on the baseline specification as well as those based on a specification that adds 10 yearly leads of each weather variable to the baseline specification. The same regression sample (which is shortened by 10 years due to the inclusion of the leads) is used in both cases. Each series (color) corresponds to a different specification. The dots for each series show the marginal effect of the weather variable indicated on the x-axis on the level of the outcome variable indicated in the panel heading. The range shown above and below the marker displays the 90 percent confidence interval based on standard errors that are two-way clustered by county and by year.

Figure A14: Time-Varying Longer-Run Marginal Effects of Weather



Notes: These plots show the estimated longer-run marginal effect of the weather variable indicated on the x-axis on the level of the outcome variable indicated in the panel heading. The underlying regression includes county and year fixed effects and interacts each weather variable with a linear time trend (year minus 1980). The blue series shows the uninteracted 30-year effects while the red series shows the implied 30-year effects as of 2020, calculated as the uninteracted 30-year effect plus the interaction coefficients times 40 (2020 - 1980). Standard errors are two-way clustered by county and by year. The range shown above and below the marker displays the 90 percent confidence interval.

Figure A15: Projected Changes in Spatial Distribution of U.S. Economic Activity from 2020 to 2050 Due to Projected Climate Changes, Based on Full Third-Order PDL Model and RCP 4.5 Scenario Allowing Weather Effects to Vary by Local Historical Climate and Income



Notes: Each map shows the projected change in the log of the indicated outcome between 2020 and 2050 due to climate change (i.e., $\Delta \widehat{y^{CC,0}_{i,2020-50}}$ from equation). The units are changes in log values, so 1.0 (-1.0) corresponds to doubling (halving) of the level of the outcome. Projections are based on estimated historical regression model that allows each weather variable's effects to vary both with the historical (1951-2020) mean of that variable in the county, which we refer to as the "local historical climate," and with historical (1969-2020) mean income in the county.