Weather Shocks and Climate Change*

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– preliminary and incomplete —

Abstract

Previous research has shown that weather shocks, i.e. temperature deviations from the long-run normal values, have significant effect on economic outcomes, such as employment or income, even in developed economies such as the United States. This evidence is often interpreted as reflecting limits to adaptation. We document large differences in the sensitivity of economic activity to weather shocks across regions within the US. We interpret these differences as reflecting adaptation choices that regions make given their specific climate. This leads us to use these reduced form estimates to estimate a simple structural model of adaptation. We can then use the model to infer the effect of projected climate change on production. We find that both the median losses and the identity of the losers from climate change vary substantially once adaptation is taken into account.

JEL codes: E23,O4,Q5,R13.

Keywords: climate change, adaptation, weather effects.

1 Introduction

Scientists predict that the world will experience significant climate change over the coming century. Average temperatures will continue to rise, leading to many consequences ranging from sea level rise, to more extreme weather events, to a changing pattern of precipitation. These in turn will affect humans in a multitude of ways. This paper is concerned with the effect that changing temperature will have on economic output. Previous research has demonstrated using reduced form panel data estimates that in today's world, temperature affects output systematically. For instance, Dell, Jones and Olken (2012) demonstrate that annual GDP is systematically lower in poor countries when their average annual temperature is higher than usual; Burke et al. (2015) expands on this to argue that the effects are actually nonlinear in temperature; and Deriyugina and Hsiang (2014) provide evidence that within the US, hot days reduce annual income. The evidence in these papers is convincing because by using country (or county) fixed effects, it controls for the average temperature (the "climate") and identifies precisely

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the effect of deviation of temperature from its normal value (the "weather" shock).[1] Using these results to infer what would happen if there were climate change requires some assumptions - most importantly, that the effect of weather will remain the same as climate changes, that is, that there is little adaptation.

Our contribution in this paper is twofold. We first present evidence of a very large heterogeneity in the sensitivity to temperature across US counties. Simply put, places that are ordinarily warm, such as the South, are largely unaffected by high temperature realizations. We interpret this evidence as reflecting adaptation: households and firms who operate in the South know its (current) climate, and consequently have made decisions to reduce the effect of hot days. On the other hand, the North has not made these same decisions, presumably because the costs entailed are too large and not justified given the climate faced by the North. This suggests that the current cross-section of US regions is informative about the cost of adaptation. Costs can be born to reduce your exposure to weather, but these costs must be worth the investment, so the model naturally ties the sensitivity to hot days with the typical number of hot days that you experience. If climate change means that Chicago will become more like New Orleans over the coming decades, we can see how New Orleans react to weather today to figure what it would imply for Chicago.

To make this comparison operative, we build a very stylized general equilibrium model that incorporates both (i) realistic weather variation, (ii) a sensitivity of the economy to weather shocks, (iii) a margin of adaptation. The unit of analysis is the county. Each county has to decide how much to invest in adaptation. Adaptation involves a cost but reduces the sensitivity of the economy to weather shocks. We estimate the key parameters of the model so that it fits the evidence discussed above, i.e. (i) the average US county is sensitive to hot days and (ii) counties with higher average temperature have a lower sensitivity. As we discuss later in detail, this approach also relies on some assumptions, chiefly that the costs of adaptation remain constant.

We have four main results. First, we find that the effect of climate change is significantly smaller if adaptation remains at the level currently available in the United States. The median income loss in a county is 7.2% without any adaptation, but 3.3% with adaptation. Second and perhaps more surprisingly, we find that the losses are much smaller even without any additional adaptation, simply taking into account the different sensitivities to weather that we observe today (i.e. the current adaptation today). In that scenario, the median losses amount to 5.4%. Third, we find that the heterogeneity in losses is significantly smaller once adaptation (either current or future) is taken into account. In the simplest calculations, a significant fraction of counties lose over 10% of their income, while this does not happen for any county under adaptation. Fourth, the geography of loser changes dramatically: without adaptation, the South appears as the main loser, but with adaptation, the Midwest is the main loser. Again, these results hold even keeping adaptation at the level currently estimated.

There are a number of caveats to our study. In terms of scope, we focus on one aspect of climate change - rising temperatures - and one outcome variable – economic production. It is quite possible that there are large economic effects of other aspects of climate change (such as rising sea levels, more frequent extreme events, etc.). It is also clear that many important outcomes beyond directly measured

[1] This finding is hence quite different from the usual observation that income is lower in hot countries - a purely cross-sectional relation which is difficult to interpret causally.

economic output will be affected (such as health). The other main caveat is that future adaptation may be more expensive than the currently available one because of various general equilibrium forces that we currently do not model. Moreover, there is some extrapolation involved for some scenarios since the temperature might rise.

1.1 Literature review

There is a growing literature in economics on climate change, pioneered by Nordhaus. Much of this literature focuses on how the economy affects climate, through the carbon cycle, and how policy should address the central pollution externality. Example recent studies along these lines include Krusell et al. (2016) or Acemoglu et al. (2016). Our paper focuses on the propagation from climate to the economy. A large empirical literature estimates the effect of weather fluctuations. Dell, Olken and Jones (2014) is a recent review of this literature. Dell, Olken and Jones (2012) offered a cross-country annual panel data analysis and demonstrated that poor countries' GDP is affected negatively by temperature, that this effect is not only agriculture driven, and that the GDP losses do not appear to be made up fully over the next couple of years. Burke et al. (2015) extend their work and emphasize that the effect of temperature appears to be nonlinear, and might hold even in rich countries. Deryugina and Hsiang (2014) provide similar evidence for the US alone at the county level. The effect of weather on other features of economic activity has also been studied in Greenstone and Deschenes (agriculture; 2013), Graff Zidin and Neidell (hours worked; 2014). Other studies in the US have demonstrated a short-run effect of weather on economic indicators (Boldin and Wright (2015), Bloesch and Gourio (2015), Foote (xxx).

The various margins of adaptation to climate change have also been studied in several papers. Some papers merely note that the short-run effect is an upper bound on the effects of weather under some conditions (e.g., Greenstone and Deschenes (2013)), while others explicitly study various mechanisms for adaptation. Greenstone et al. (2015) demonstrate that mortality is now less sensitive to hot days and link this to the development of AC technology. but there are few papers that explicitly model this choices. [Add papers studying agriculture; Add: Colacito, Hoffman and Phan.]

2 Evidence

This section measures the short-run effect of weather on US economic activity at the county-level using simple reduced-form techniques, and how that effect varies with counties' characteristics. Our approach follows closely Deriyugina and Hsiang (2014).

2.1 Data

We assemble data as Deriyugina and Hsiang (2014) by merging at the county-year level income statistics created by the Bureau of Economic Analysis (BEA) and measures of temperature, precipitation and snowfall built from the National Centers for Environmental Information (NCEI, formerly NCDC) an entity of NOAA. The income statistics are compiled from the BEA and provide a measure of total personal income per capita as well as its breakdown between wages, wage supplements, transfers, proprietor income, and capital income (dividends, interest and rent). The weather statistics are constructed using the US-HCN (historical climate network) database that collect daily measures at the weather station level. Temperature is defined as the average of the max and min temperature that day. We then aggregate to the county-level through a simple average of all weather stations located in a county.[2] Our final sample is an unbalanced sample of 2,901 counties over the period 1969-2015.[3] Table 8.1.1 in appendix presents summary statistics of the key variables used in the analysis.

2.2 Baseline Results without Heterogeneity

Our baseline specification is

$$\Delta \log Y_{i,t} = \alpha_i + \delta_t + \sum_{k=1}^{K} \beta_k Bin_{k,i,t} + \varepsilon_{i,t}, \tag{1}$$

where $\Delta \log Y_{i,t}$ is the growth rate of income in county i in year t, α_i is a county fixed effect and δ_t a time fixed effect, and $Bin_{k,i,t}$ is the number of days in year t in county i where the temperature T falls in bin $k = 1...K$. The central bin (12C-15C) is omitted, and hence provides a reference by comparison to which temperature deviations are evaluated. Following Deriyugina and Hsiang (2014) we use $K = 17$ bins to capture possibly nonlinear effects of temperature on income.[4] This specification is attractive because weather variation from one year to next is quasi-random. The presence of county fixed effects means that we are, in effect, comparing income growth in the same county in two years that differ in their distribution of days across bins. Figure 1 depicts the results, and Table 2.2 presents coefficient estimates and the associated standard errors in column 1.[5] Consistent with Deriyugina and Hsiang (2014), we find that the number of hot days (above 30C, or between 27C and 30C) affects negatively income in the county. An additional day in the upper bin relative to the reference bin (12C-15C) reduces annual income by about 0.05%. This is a large effect, because one day corresponds only to 1/365=0.27% of annual time. If income was generated linearly across the year, then the reduction of income due to this hot day amounts to a 18% reduction in income (0.05/0.27). This is very large effect.[6]

[2] In untabulated results, we used an alternative approach - rather than averaging all stations in a county, we weight all stations (inside and outside the county) according to their inverse squared distance to the county's centroid. We obtained similar results.

[3] The sample starts in 1969 because this is when the BEA data start.

[4] Our specification differs from that paper only in that we use the log change of income per capita as the dependent variable. They use the log (level) of income per capita, and add the lagged level as a control. Our calculation of standard errors also differs slightly. Based on Abadie et al. (2017), we believe it is more appropriate to cluster standard errors twoway by state and the interaction of NOAA region and year. This is because the treatement (temperature) is correlated across states within a year, at least within the NOAA region (a hot year in Illinois is also likely to be a hot year in Iowa). The resulting standard errors are somewhat larger.

[5] Our calculation of standard errors also differs slightly from that of Deriyugina and Hsiang (2014). Based on Abadie et al. (2017), we believe it is more appropriate to cluster standard errors twoway by state and the interaction of NOAA region and year. This is because the treatement (temperature) is correlated across states within a year, at least within the NOAA region (a hot year in Illinois is also likely to be a hot year in Iowa). The resulting standard errors are somewhat larger.

[6] Note, however, that in some cases income is not generated linearly across the year; for instance in some circumstances a day too hot might kill crops, reducing significantly the entire annual output. In that case we would find a reduction of

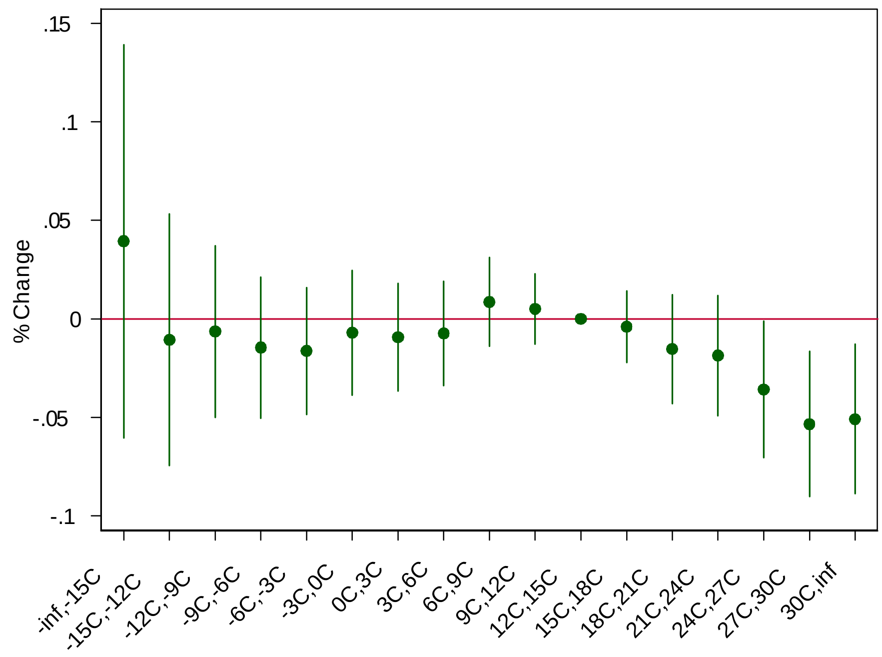

Figure 1: The circles denote estimates of β_k in equation (1), and the bars reflect the associated +/- 2 standard error bands.

The appendix reports several variants and robustness of this basic result. We show in particular that (1) the effects are reversed the following year but might not be fully eliminated, (2) the results are concentrated on weekdays, (3) the results are concentrated on farm proprietary income.[7]

2.3 Heterogeneity in Sensitivity

We next proceed to study the heterogeneity across regions in the sensitivity to temperature. Our main result is that this heterogeneity is much smaller in places with high average temperature. We first show this result using a simple subsample analysis, then we show a more complex interaction models, and finally we use a random coefficient (multilevel) model to establish this result.

2.3.1 Subsample analysis

Our first approach simply involves dividing all counties into five quantiles of the annual average temperature, and estimating our baseline regression separately for each quintile. Results are shown in table 2.2 and depicted in figure 2. We observe a considerable dispersion in the sensitivity to hot days. Counties in the first quintile have a sensitivity of around -0.5, which is imprecisely estimated because these counties have few hot days. In the second quintile the sensitivity is similar but precisely estimated (the t-stat is close to four). In the third quintile, the coefficient is halved, around -0.25, but it remains highly statistically significant. In quintile four, the coefficient drops to -0.01, which is indistinguishable from

production greater than a 100% for a hot day.

[7] It might seem contradicatory that the effects are largely driven by farm and by weekdays. It turns out that, while for farm income the effects are similar on weekdays and weekends, as might be expected, wages and salaries actually increase with temperature on weekends, creating the difference.

	Baseline	Quintile 1	Quintile 2	Quintile 3	Quintile 4	Quintile 5
-15C or less	0.0394	0.00707	0.0647	0.0868	-0.111	0.0304
	(0.80)	(0.14)	(1.09)	(0.93)	(-0.60)	(0.46)
-15C,-12C	-0.0107	-0.0792*	-0.0280	0.0659	0.188	-0.604*
	(-0.34)	(-2.37)	(-0.48)	(1.04)	(1.55)	(-2.49)
-12C,-9C	-0.00638	-0.0629*	-0.00976	0.0620	-0.0166	0.430*
	(-0.29)	(-2.02)	(-0.27)	(1.15)	(-0.22)	(2.26)
-9C,-6C	-0.0146	-0.0391	-0.0429	0.00257	-0.0121	0.142
	(-0.82)	(-1.62)	(-1.78)	(0.06)	(-0.33)	(1.26)
-6C,-3C	-0.0163	-0.0625**	-0.0179	-0.00763	-0.0136	-0.0909
	(-1.01)	(-2.84)	(-0.75)	(-0.24)	(-0.44)	(-1.54)
-3C,0C	-0.00704	-0.0586*	-0.0223	0.0143	0.0294	-0.0435
	(-0.45)	(-2.61)	(-0.92)	(0.47)	(1.30)	(-1.62)
0C,3C	-0.00932	-0.0435	-0.0197	0.00331	0.0170	0.0167
	(-0.69)	(-1.89)	(-0.97)	(0.12)	(0.95)	(0.93)
3C,6C	-0.00739	-0.0226	-0.00585	-0.0113	0.00342	0.00822
	(-0.56)	(-1.04)	(-0.26)	(-0.39)	(0.18)	(0.42)
6C,9C	0.00859	0.00836	0.00544	0.0213	-0.0136	0.00189
	(0.77)	(0.42)	(0.22)	(0.73)	(-1.09)	(0.12)
9C,12C	0.00505	0.00423	-0.0123	0.0127	0.00437	-0.00281
	(0.57)	(0.20)	(-0.66)	(0.55)	(0.33)	(-0.25)
15C,18C	-0.00400	-0.0116	0.0202	-0.00446	-0.00703	-0.00469
	(-0.44)	(-0.57)	(1.14)	(-0.25)	(-0.44)	(-0.34)
18C,21C	-0.0153	-0.0656*	-0.0254	0.00692	-0.00188	0.0109
	(-1.12)	(-2.49)	(-1.11)	(0.28)	(-0.12)	(0.70)
21C,24C	-0.0186	-0.0401	-0.0366	-0.0238	0.000826	0.00653
	(-1.23)	(-1.28)	(-1.61)	(-0.86)	(0.05)	(0.54)
24C,27C	-0.0358*	-0.0781	0.00268	0.00321	-0.00210	0.0132
	(-2.08)	(-1.77)	(0.09)	(0.13)	(-0.12)	(0.95)
27C,30C	-0.0534**	-0.277*	-0.160**	-0.0518	-0.0222	0.00388
	(-2.92)	(-2.10)	(-2.79)	(-1.41)	(-1.22)	(0.29)
30C or more	-0.0508**	-0.486	-0.503***	-0.234**	-0.0101	0.0169
	(-2.70)	(-1.30)	(-3.97)	(-3.51)	(-0.38)	(1.04)
N	90529	18145	18140	18073	18106	18065

Table 1: Estimates of the baseline specification for the entire sample (column 1) and for each quintile of counties, sorted by their average temperature. All regressions include county and time fixed effects. Standard errros clustered by year. Stars indicate statistical significance at the 10 percent (*), 5 percent (**) and 1 percent (***) level.

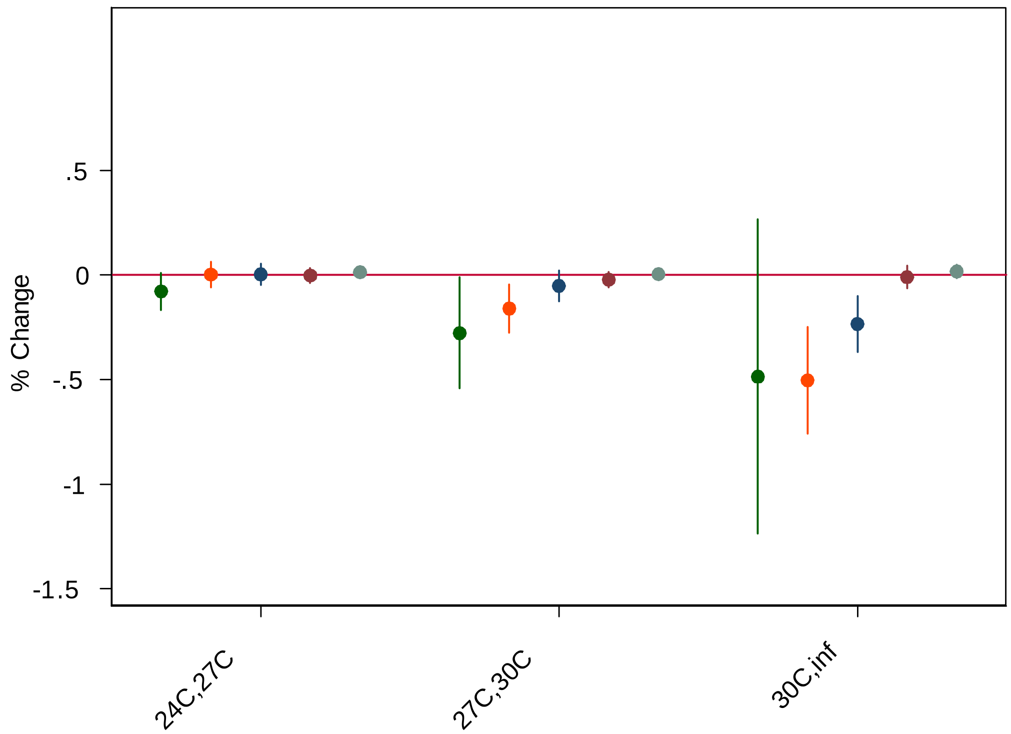

Figure 2: The circles denote estimates of β_k in equation (1) for $k = 15, 16, 17$ (three hottest temperature bins), for each of the five groups of counties (quintiles ordered by average temperature), and the bars reflect the associated +/- 2 standard error bands.

zero, and in quintile five, the point estimate is positive, though not significantly. Economically, the last two quintiles have a fairly precisely estimated sensitivity close to zero.

2.3.2 Interaction model

One concern with the subsample analysis is that average temperature might be correlated with other characteristics that affect the sensitivity to weather, for instance income. To rule this out, we estimate a model where the coefficients on the temperature bins are allowed to vary with the average temperature of the county, $\overline{T_i}$. We then incorporate other factors. The general form of this model is:

$$\Delta \log Y_{i,t} = \alpha_i + \delta_t + \sum_{k=1}^{K} \left(\sum_{l=0}^{L} \beta_{kl} x_{ilt} \right) Bin_{k,i,t} + \varepsilon_{i,t}, \tag{2}$$

where x_{ilt} are factors that might affect the sensitivity of the county to weather. Our baseline model above (equation 1) uses only a constant in x_{ilt} Figures 3, 4 and 5 report the marginal effect of a hot day (that is, the overall effect of having a day in the last bin, with temperature above 90C) for three alternative models that include variables in x_{ilt} in addition to the constant: (i) the quadratic model includes $\overline{T_i}$ and $\overline{T_i}^2$ (ii) the cubic model includes $\overline{T_i}$ and $\overline{T_i}^2$ and $\overline{T_i}^3$; (iii) the quadratic-year-income model includes $\overline{T_i}$ and $\overline{T_i}^2$ as well as time and log county income.

The results confirm that there is a very large decline in the sensitivity to hot days as the average temperature rises. For the warmest US counties, it is impossible to reject that this effect is zero (and it

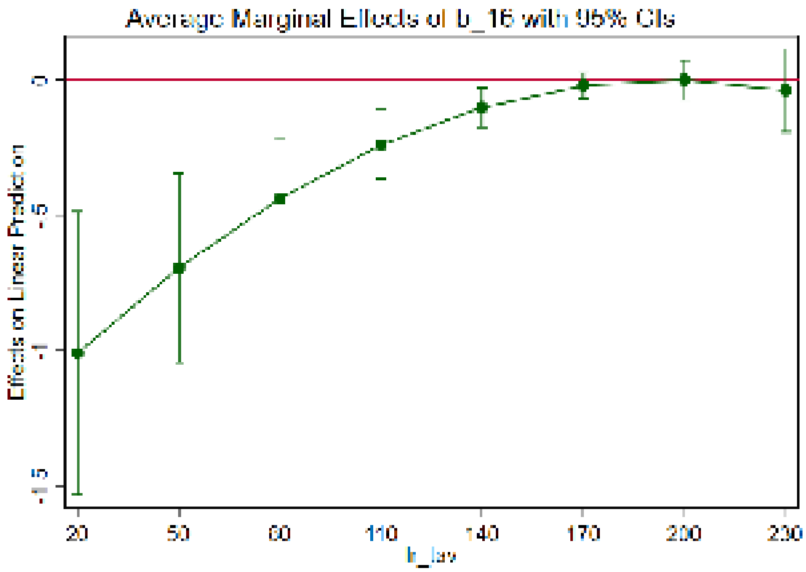

Figure 3: The figure plots the estimated marginal effect of a hot day from model (2), for different values of the average temperature of the county $\overline{T_i}$. Quadratic model.

is fairly precisely estimated). Moreover, the effects are fairly similar across specifications; in particular, controlling for income has a fairly small effect on this result.

2.3.3 Random coefficient

The results in this section are highly preliminary. We estimate a simpler specification focusing on the effect of hot days (bin K=17) using a random coefficient model:

$$\Delta \log Y_{i,t} = \alpha_i + \gamma_i Hot\_Days_{i,t} + \varepsilon_{i,t}, \tag{3}$$

where α_i and $\beta_{K,i}$ are now both random effects (and $Hot\_Days_{i,t} = Bin_{K,i,t}$). For more statistical power, we pool by state, i.e. we assume the slope coefficient is constant by state:

$$\Delta \log Y_{i,t} = \alpha_{s(i)} + \gamma_{s(i)} Hot\_Days_{i,t} + \varepsilon_{i,t}, \tag{4}$$

where $s(i)$ is the state of county i. This leads to a mean slope of -0.203 with a standard deviation of this

slope of 0.046. Figure 6 depicts the filtered slopes against the average temperature of the State. Again, we see that cooler States have a much larger (in absolute value) sensitivity.

2.3.4 Summary target for estimation

In order to provide a simple summary target for structural estimation, we estimate the simple regression of income growth on the number of hot days, and run it for each quintile of average temperature separately:

$$\Delta \log Y_{i,t} = \alpha_i + \delta_t + \gamma Hot\_Days_{i,t} + \varepsilon_{i,t}. \tag{5}$$

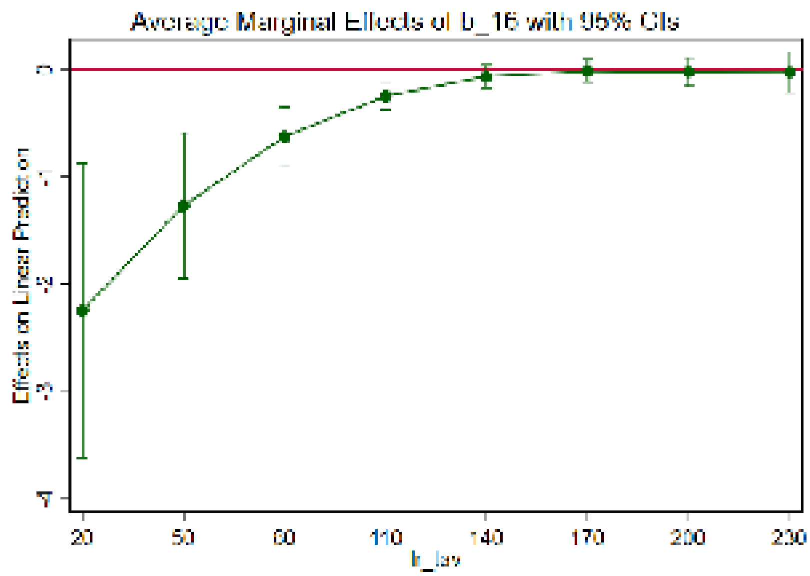

Figure 4: The figure plots the estimated marginal effect of a hot day from model (2), for different values of the average temperature of the county $\overline{T_i}$. Cubic model.

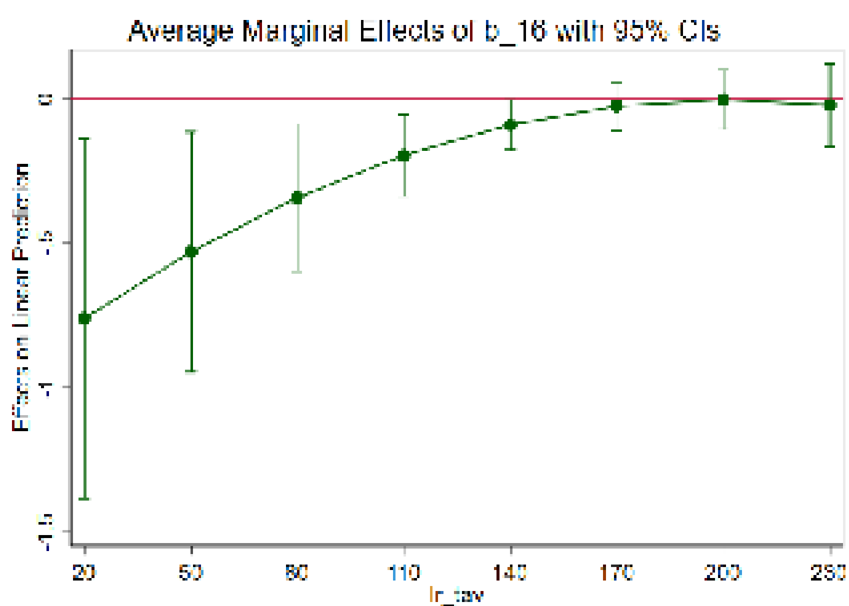

Figure 5: The figure plots the estimated marginal effect of a hot day from model (2), for different values of the average temperature of the county $\overline{T_i}$. Quadratic-year-income model.

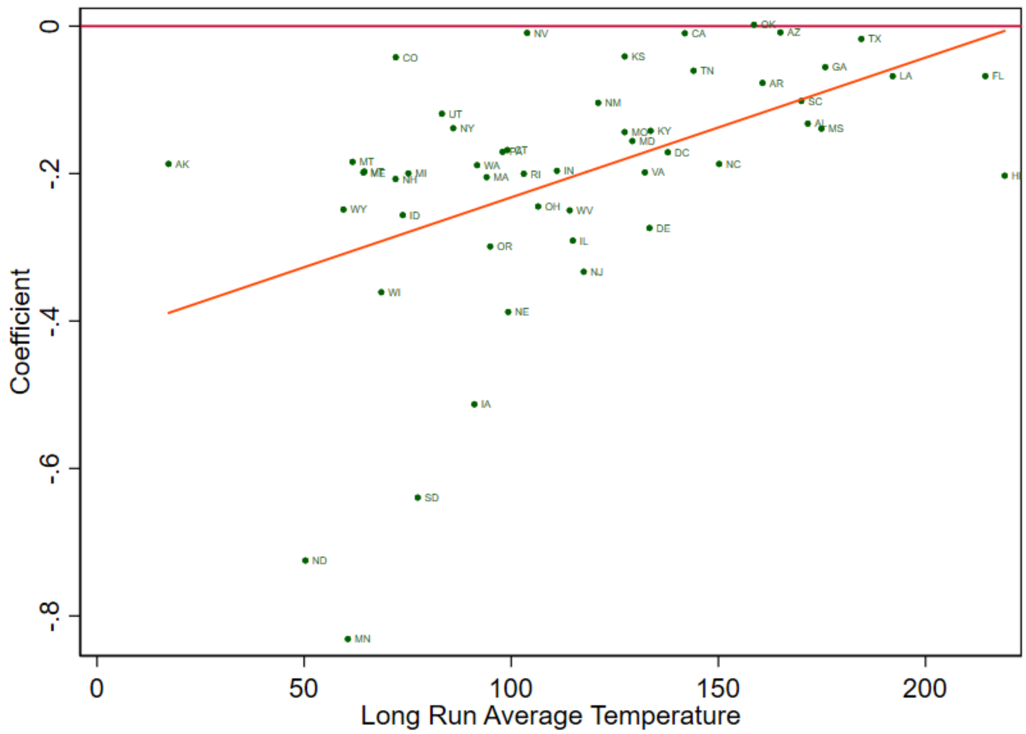

Figure 6: The figure plots the estimates of a random coefficient model from equation (4), pooled by state, against the average temperature of the state.

	Q1	Q2	Q3	Q4	Q5
γ	-0.136	-0.071	-0.086	-0.039	-0.006
s.e.	0.058	0.019	0.009	0.005	0.003

Table 2: Estimates of equation 5 separately for each quintile of average temperature. Standard errors clustered by year.

The estimates in table 2.3.4 provide a simple summary statistic of the heterogeneity across regions.

3 Structural Model

This section presents the structural model we use for our counterfactuals. The model captures the effect of temperature on productivity, and allows for an endogenous adaptation margin whereby counties can invest to reduce their exposure to temperature. First, we present the model assumptions and solution. Second, we estimate the model to replicate some of the empirical results obtained in the previous section.

3.1 Model description

The model is essentially a standard real business cycle model (without capital) where variation in productivity is driven by temperature. The economy is made up of a fixed finite number of independent counties. Each county is an isolated island; there is no trade nor population migration. The county's population produces output using a decreasing return to scale production function:

$$Y_{it} = A_{it} N_{it}^{\alpha},$$

where A_{it} is total factor productivity in county i at time t, N_{it} is labor supplied, and Y_{it} is output. Given that there is trade and no capital, the resource constraint of county i reads:

$$C_{it} = Y_{it}.$$

The county has a representative household with standard preferences:[8]

$$E \sum_{t=0}^{\infty} \beta^t \left(\frac{C_{it}^{1-\gamma}}{1-\gamma} - \frac{N_{it}^{1+\psi}}{1+\psi} \right).$$

Motivated by the empirical patterns of Section 2, we assume that productivity depends on temperature above a threshold temperature $\overline{T}$ as follows:

$$\begin{aligned} \log A_{it} &= b_0 \text{ if } T_{it} < \overline{T}, \\ &= b_0 - b_1(k)(T_{it} - \overline{T}) \text{ if } T_{it} \geq \overline{T}. \end{aligned}$$

Here b_0 is the baseline productivity, assumed constant over time and across counties. (Given our empirical approach, this simplification is without loss of generality.) The parameter $\overline{T}$, assumed constant across counties, is the temperature past which productivity starts to fall; and finally $b_1(k)$ is the rate at which productivity falls above $\overline{T}$. This rate is endogenously chosen as we will explain shortly.

The temperature T_{it} is iid over time and is drawn from a (constant) county-specific cumulative distribution function $F_i(.)$.[9] This temperature distribution is the only exogenous difference across counties in our model: they are endowed with different climate; all other parameters are identical.

For simplicity we assume that the time period is a day. This provides an easy mapping between the model and the reduced form work.[10]

We next turn to the modeling of adaptation. We assume that the representative household can choose to pay a cost to reduce its sensitivity b_1 to weather. The cost k reduces output in all states of natures, but it also reduces the negative effect of high temperature on productivity. Mathematically, paying a cost k leads to $b_1 = b_1(k)$, with $b_1 < 0$ and $b_1' > 0$, and the resource constraint is modified to

$$C_{it} = Y_{it} \times (1 - k).$$

[8] For now we abstract from the effect of weather on labor disutility; it is easy to incorporate, but estimating it requires measuring precisely the employment response to weather, whereas our work so far has only estimated the effect on income.

[9] Note that since there are no economic links between counties, the correlation across counties of temperature is immaterial for our purpose.

[10] Of course, the iid assumption for T_{it} is not true at the daily frequency, and there is seasonality within the year as well. These would not affect our results however given that the model responses are independent of the past. A more serious concern is whether the preferences and technologies are adequate representation of behavior at the daily frequency; that is, there might be important nonseparabilities across time in utility or production function.

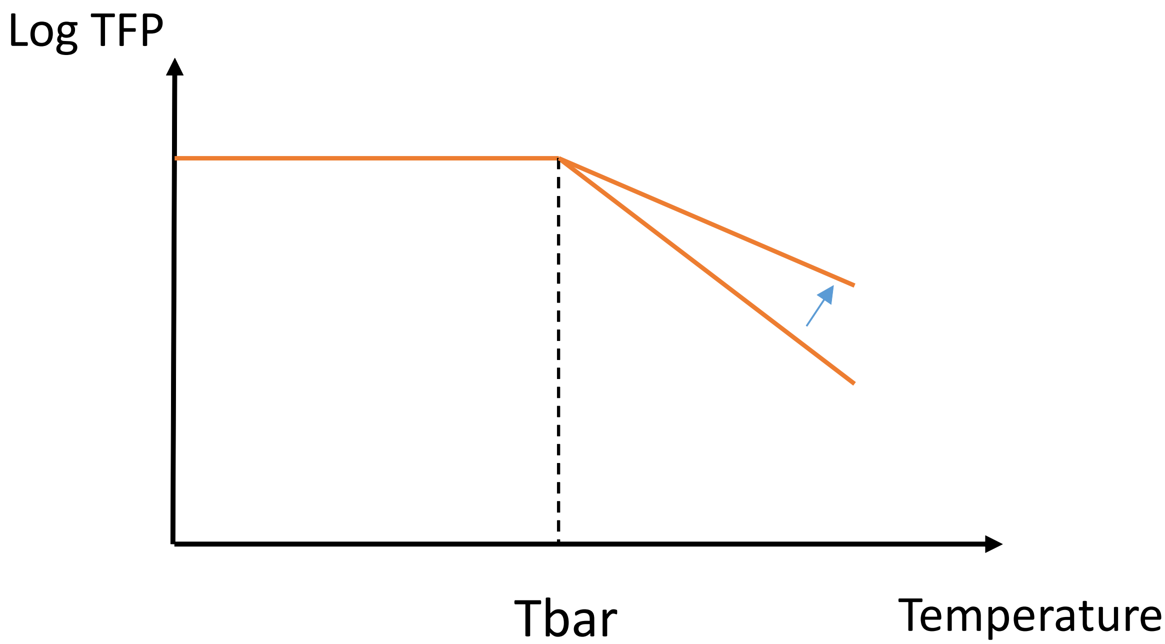

Figure 7: This figure illustrates the relationship between temperature and productivity assumed in our model. The arrow depicts the effect of investment in adaptation.

Importantly, this cost is a once-and-for-all choice made at time 0. The representative household makes this choice, knowing the distribution of future temperature $F_i(.)$, and cannot change it at any point thereafter.

3.2 Model solution

The model can be solved easily given its tractability. The first step is to calculate output, labor and consumption for a given choice of adaptation and a given realization of productivity (i.e. temperature). Next, we can solve for the optimal level of adaptation. Since counties do not interact, we can solve each county's equilibrium independently.

To solve for the equilibrium given adaptation and a realization of temperature, we simply write the first order condition equating the MRS between consumption and leisure and the marginal product of labor:

$$N_{it}^{\psi} C_{it}^{\gamma} = (1-k)\alpha A_{it} N_{it}^{\alpha-1},$$

where $C_{it} = (1-k)A_{it}N_{it}^{\alpha}$; this leads to a closed form solution for labor

$$N_{it} = \left(\alpha(1-k)^{1-\gamma} A_{it}^{1-\gamma}\right)^{\frac{1}{1+\psi+\alpha(\gamma-1)}},$$

hence

$$Y_{it} = (1-k)A_{it}\left(\alpha(1-k)^{1-\gamma} A_{it}^{1-\gamma}\right)^{\frac{\alpha}{1+\psi+\alpha(\gamma-1)}} = ((1-k)A_{it})^{\frac{1+\psi+2\alpha(1-\gamma)}{1+\psi+\alpha(\gamma-1)}} (\alpha)^{\frac{\alpha}{1+\psi+\alpha(\gamma-1)}}.$$

this can be conveniently expressed in log as:

$$\log N_{it} = \frac{1-\gamma}{1+\psi+\alpha(\gamma-1)} \log A_{it} + \text{constant}, \tag{6}$$

$$\log Y_{it} = \frac{1+\psi+2\alpha\,(1-\gamma)}{1+\psi+\alpha(\gamma-1)} \log A_{it} + \text{constant}. \tag{7}$$

We can then evaluate numerically the expected utility of a county that has climate F_i and chooses adaptation k. It is the value:

$$\begin{aligned} V(k;F_i) &= \max_{N_{it}} E \sum_{t=0}^{\infty} \beta^t \left(\frac{C_{it}^{1-\gamma}}{1-\gamma} - \frac{N_{it}^{1+\psi}}{1+\psi} \right), \\ s.t. &: \quad Y_{it} = A_{it}(k, T_{it}) N_{it}^{\alpha} \text{ and } T_{it} \ \rightarrow F_i(.), \end{aligned} \tag{8}$$

and given that the environment is static, this can be simplified as

$$\frac{1}{1-\beta} E \left(\frac{(A_{it} N_{it}^{\alpha} (1-k))^{1-\gamma}}{1-\gamma} - \frac{N_{it}^{1+\psi}}{1+\psi} \right),$$

where N_{it} is given by equation (6) and the expectation is taken over T_{it}, drawn according to F_i. In practice, we discretize the distribution F_i using probability π_{is} and mass points ω_{is}, for $s = 1...S$, which allows us to calculate this value as

$$V(k;F_i) = \frac{1}{1-\beta} \sum_{s=1}^{S} \pi_{is} \left(\frac{(A(k;\omega_{is}) N(k;\omega_{is})^{\alpha} (1-k))^{1-\gamma}}{1-\gamma} - \frac{N(k;\omega_{is})^{1+\psi}}{1+\psi} \right).$$

We finally find the optimal adaptation choice as

$$k^* = \arg\max_k V(k;F_i), \tag{9}$$

In practice we discretize the choice of k to make the solution of the problem more robust, but we consider a grid large enough that discreteness has no impact on the results.

3.3 Model estimation

Our very simple model captures the margin of adaptation which is critical for thinking about the effect of climate change. The challenge is to estimate the parameters that govern adaptation. Here we ask the model to reproduce the heterogeneity in the currently observed sensitivities to weather shocks - that is, to match the adaptation levels we observe across the US.

Our parameter choices works as follows. We preset some parameters based on previous research or commonly agreed macro elasticities. We then pick the two critical parameters - that govern how much temperature affects productivity and how much it costs to reduce the sensitivity b_1 by replicating some key features of the data. Specifically, we target the regressions coefficient of quintiles 1, 3 and 5 of table 2.3.4.

Our preset parameters are listed in table 3.3. We use a standard macro elasticities of one for consumption and leisure. Our final results are relatively insensitive to these parameters. We set the labor share to 0.7. Based on the evidence above, we set $\overline{T}$, the threshold temperature, to 24C.

symbol	value	meaning	
β	irrelevant	discount factor	preset
γ	1	consumption IES	preset
ψ	1	labor supply IES	preset
α	0.7	labor share	preset
$\overline{T}$	24C	threshold	preset
$\overline{b_1}$	.143	sensitivity of TFP to temperature above $\overline{T}$	estimated
θ	46.18	effectiveness of adaptation	estimated

Table 3: Parameters used in the model.

	Q1	Q3	Q5
Data	-0.136	-0.086	-0.006
Model	-0.136	-0.079	-0.025

Table 4: Summary statistics.

The two parameters we estimate are linked to the sensitivity function $b_1(k)$. We assume a functional form[11]

$$b_1(k) = \overline{b_1}e^{-\theta k}.$$

The parameter $\overline{b_1}$ captures the sensitivity of productivity to temperature above $\overline{T}$ without adaptation ($k = 0$). The parameter θ measures the efficiency with which the adaptation cost k translates into a smaller (in absolute value) sensitivity. That is, θ measures the cost of adaptation.

Table 3.3 shows the targeted moments along with the values obtained in the model for the parameters that deliver the best fit. The model matches fairly well the three moments. The values of $\overline{b_1}$ and θ that generate this behavior are listed in 3.3. The estimated $\overline{b_1}$ is very large, as is necessary to fit the data that high temperature has large effect in some regions. The estimated θ is not extremely large: reducing the sensitivity by 1% (i.e., from 0.143 to 0.143*.99=0.1416) costs 0.02% of income. Reducing the sensitivity by 50% costs 1.5% of income.[12] Yet these costs are still large enough to make the quintile 5 more sensitive to temperature than in the data.

4 Counterfactuals

We now use the model to generate counterfactual predictions to climate change. We feed in the model the predicted climate change and ask two questions: (1) how large will the income losses from climate

[11] We have experimented with alternative functional forms and obtain broadly similar results.

[12] Since $\log(0.5)/\theta = -0.015$

change be? (2) which regions in the US will be most affected? The first describes how we perform these counterfactuals, and the second section presents out results.

4.1 Assumptions

Our calculations require two inputs: first, a climate forecast by county over the next century; and second, a model that maps temperature into income. Regarding the climate forecast, we use a very simple starting point and assume that all counties will experience an equal increase in temperature of 5.1C. We base this on the study by Rasmussen et al. (2016). There is relatively little heterogeneity across counties in the temperature increase, which motivates our simplification. However, we plan to relax this in the future and consider (a) increases in mean temperatures that are different across counties and (b) changes in the distribution beyond the increase in the mean.

Regarding the model used, we find it useful to contrast three different "models", which are nested in our structural model. A first model has no adaptation choice (e.g., $\theta = \infty$). This model implies that all US counties have the same sensitivity to weather. This simple model is similar to the calculations that Hsiang et al. (2017) perform for a large class of models. We call this the no adaptation model. A second model has fixed adaptation; that is, we assume that the structural model is true in that each county has, so far, chosen its adaptation optimally given its climate, but that for unmodelled reasons it is not possible to change the adaptation level from now on (perhaps because the cost of adaptation in the future will increase dramatically). This second model is essentially equivalent to a reduced form calculation, but one that takes into account the heterogeneity across counties in terms of slopes. We call this the fixed adaptation model. The third model is our full structural model, so that counties can choose given climate change to adjust their level of adaptation. We call it the endogenous adaptation model.

4.2 Results

Table 4.2 presents the estimate of the effect of climate change in output across US counties, for each of the three different scenarios (No adaptation, Fixed adaptation, and Endogenous adaptation). Several results stand out.

First, under the cost of climate change through this hot days channel is large under the no adaptation model: the median county loses about 7.2%. Second, the median losses are significantly smaller in the fixed adaptation case - which merely states that the counties that will experience more hot days according to climate science are also those that today appear less sensitive to hot days. Third, if adaptation is reoptimized in the future as it was in the past, as the endogenous adaptation model assumes, the losses will be even smaller, around 3.30% for the median county. Interestingly, these losses will occur despite an increase in production by 1.36%. The difference between the two reflects the lost output to adaptation.

Turning to the heterogeneity of losses, the remarkable result is that models which incorporate some adaptation reduce substantially the heterogeneity of losses. The standard deviation across counties of the losses is only 0.9% in the endogenous adaptation case, whereas it is 4.1% in the no adaptation case. This is in turn largely due to a reduction in the worst case scenario: 10% of counties exhibit a loss

	change in	median	sd	p10	p25	p75	p90
No adaptation	C, Y	-7.18	4.11	-12.92	-10.18	-4.34	-2.33
Fixed adaptation	C, Y	-5.40	2.06	-7.97	-6.74	-4.21	-3.18
Endogenous adaptation	C	-3.30	0.90	-4.26	-3.95	-2.70	-2.24
	Y	1.36	2.18	-1.50	-0.68	3.24	4.38

Table 5: Estimated effect of climate change on income under different scenarios of adaptation. The statistics report the cross-sectional losses across counties.

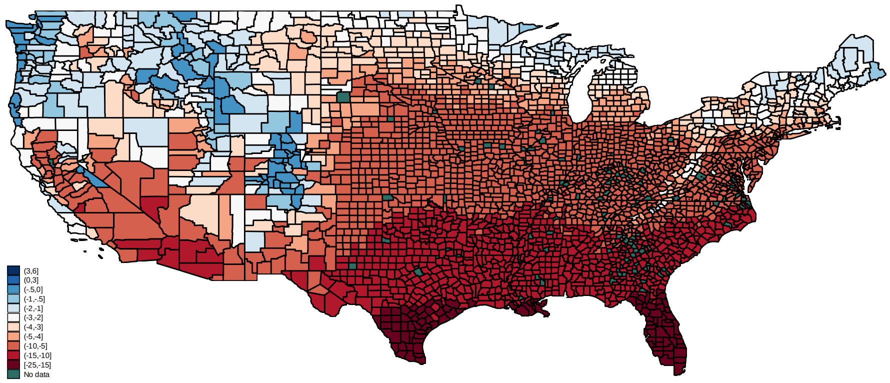

Figure 8: This figure depicts the estimated loss of income per county due to climate change in the "no adaptation" model.

greater than 12.9% in the no adaptation case. In contrast, 10% of counties exhibit a loss greater than 4.3% in the endogenous adaptation case. The logic is that adaptation allows to respond to climate change in the places where it is very costly. But it is interesting, and perhaps surprising, how reduced are the losses simply by taking into account the heterogeneity in currently-observed sensitivities.

Hence, the first finding is that adaptation (even of the plain fixed type) reduces significantly the losses. The second finding - that who loses most from climate change depends substantially on adaptation - can be seen most easily on the maps presented in Figures 8, 9 and 10. Under the no adaptation model, the South of the US suffers dramatically from climate change, because it experiences a large number of hot days, which are estimated (based on the entire US sample) to have a strong effect on income. Under the fixed adaptation model, areas in the South are markedly less affected. This calculation simply takes into account that, as of today, hot days do not seem to affect output in these areas substantially. Interestingly, it is the Midwest that seems to suffer most. Finally, under the endogenous adaptation model, all areas experience smaller losses, but again the Midwest is relatively more hit.

Another way to understand the logic of the endogenous adaptation model is to see its implications for adaptation costs and the sensitivity to weather. Figure 11 presents for each county the optimal adaptation k today and after climate change. Almost all counties increase adaptation. Many counties that currently have little adaptation would increase it significantly. These counties would bear substantial

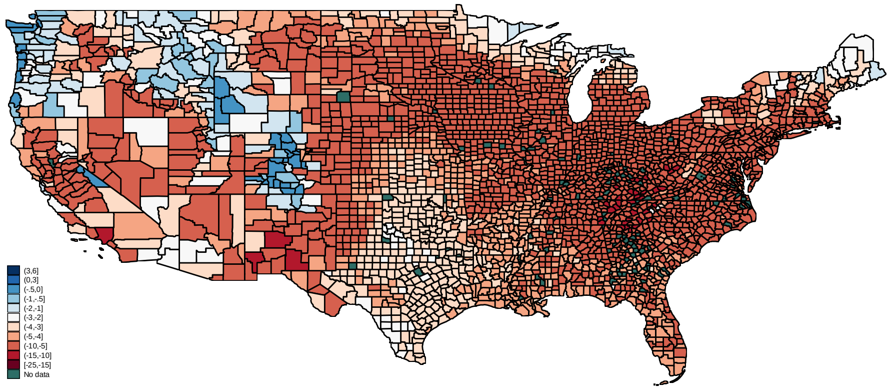

Figure 9: This figure depicts the estimated loss of income per county due to climate change in the "fixed adaptation" model.

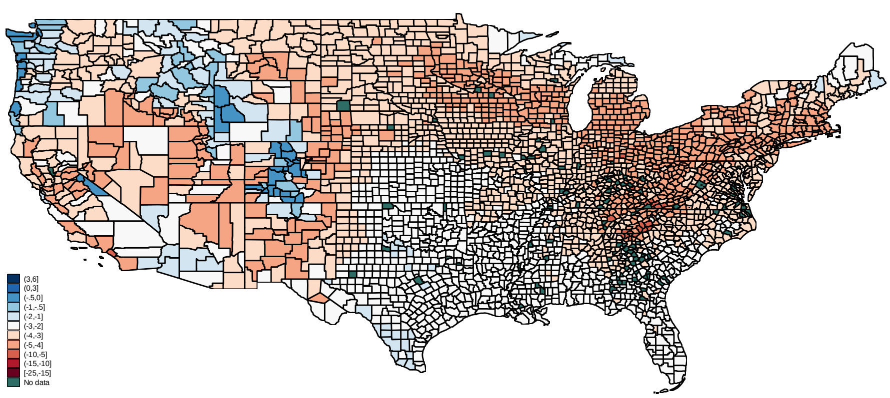

Figure 10: This figure depicts the estimated loss of income per county due to climate change in the "endogenous adaptation" model.

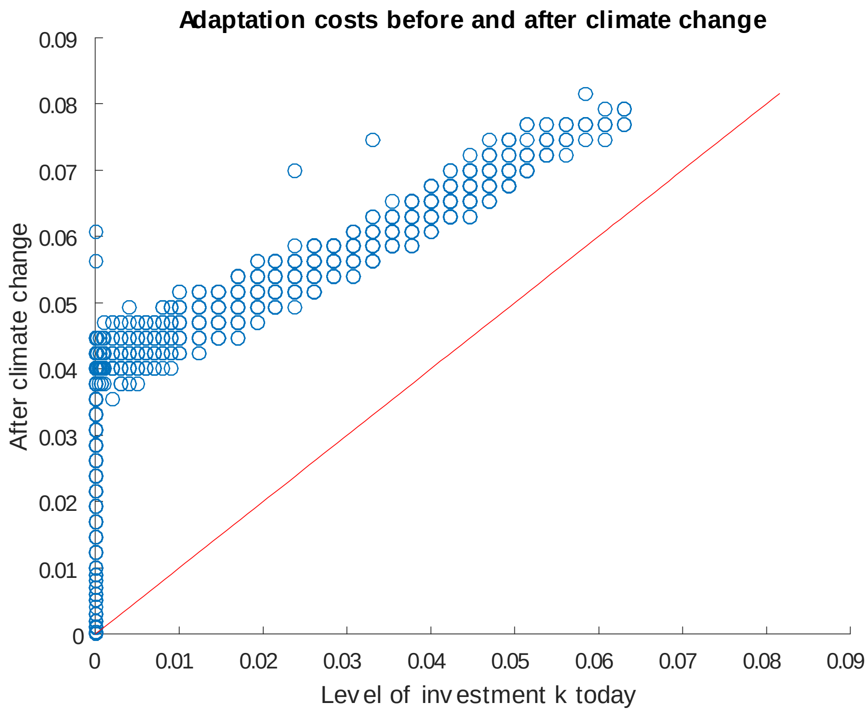

Figure 11: This figure plots the adaptation chosen by each county in the current climate (x-axis) against the adaptation it will choose after climate change (y-axis) according to the structural model.

costs. Figure 12 depicts the sensitivity $b_1(k)$ to hot temperature before and after climate change. The big chunk of counties that move from zero adaptation to something positive are reflected in the vertical scatter at the very right of the panel.

5 Work-in-progress

We are currently working to extend the model to take into account some margins that we have ignored so far, such as capital accumulation, as well as trade and migration between counties. We are also exploring different approaches to modeling adaptation. We are also exploring the effect of low temperature rather than high temperature in more detail. We are improving the exact climate change assumed in the counterfactuals.

6 Conclusion

TBA

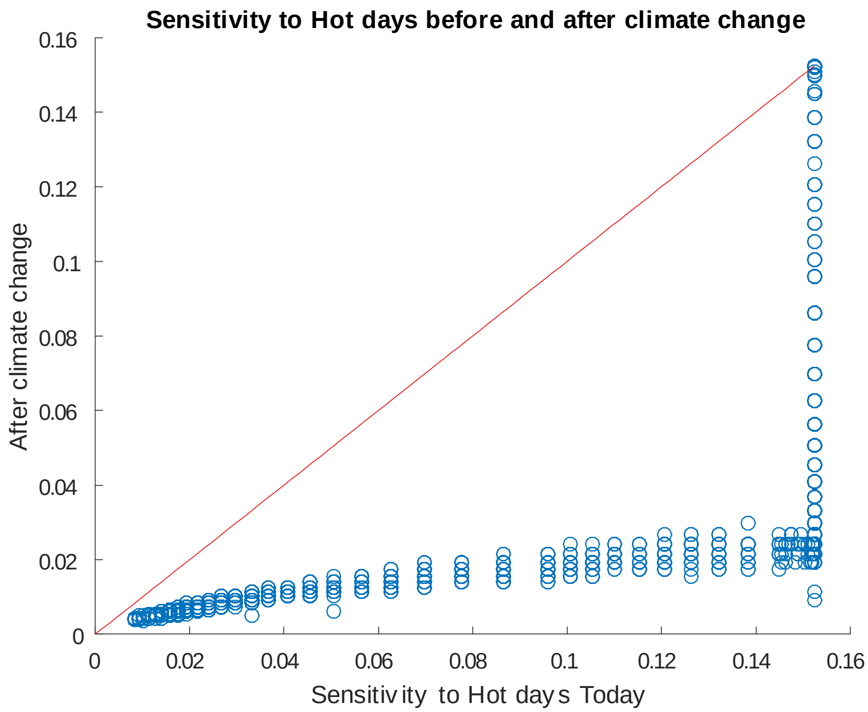

Figure 12: This figure plots the sensitivity to temperature of each county in the current climate (x-axis) against its sensitivity after climate change (y-axis) according to the structural model.

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8 Appendix

8.1 Additional empirical results

8.1.1 Summary Statistics Table

8.1.2 Station statistics

Figure 13 depicts the number of stations used in our dataset to construct our measures of weather. Figure 14 shows the locations of the stations used for 2000 (as an example).

8.1.3 Current climate

Figure 15 depicts the average annual temperature and figure 16 depict the average annual number of "hot days" for each US county. TO BE ADDED: A FIGURE AFTER CLIMATE CHANGE.

	mean	sd	min	p5	p50	p95	max	count
-15C or less	4.87	10.50	0.00	0.00	0.00	26.00	178.00	92738
-15C,-12C	3.48	4.95	0.00	0.00	1.00	14.00	45.00	92738
-12C,-9C	5.67	6.62	0.00	0.00	3.00	19.00	55.00	92738
-9C,-6C	8.77	8.53	0.00	0.00	7.00	24.00	73.00	92738
-6C,-3C	13.26	10.66	0.00	0.00	13.00	31.00	74.00	92738
-3C,0C	19.42	12.81	0.00	0.00	20.00	40.00	88.00	92738
0C,3C	24.63	13.47	0.00	2.00	25.00	47.00	117.00	92738
3C,6C	29.26	12.51	0.00	8.00	29.00	49.00	132.00	92738
6C,9C	30.86	11.20	0.00	16.00	30.00	49.00	134.00	92738
9C,12C	32.16	10.45	0.00	19.00	31.00	49.00	154.00	92738
-15C,-12C0	0.00	0.00	0.00	0.00	0.00	0.00	0.00	92738
15C,18C	33.87	10.06	0.00	20.00	33.00	49.00	157.00	92738
18C,21C	37.60	12.31	0.00	20.00	38.00	55.00	306.00	92738
21C,24C	36.30	16.46	0.00	4.00	37.00	60.00	276.00	92738
24C,27C	31.13	24.15	0.00	0.00	29.00	73.00	223.00	92738
27C,30C	17.43	23.44	0.00	0.00	6.00	68.00	169.00	92738
30C or more	3.11	9.38	0.00	0.00	0.00	18.00	130.00	92738
DL_PerCapPIncome	5.54	6.80	-107.49	-3.30	5.11	15.27	130.48	90568
DL_WageSal	5.74	6.41	-105.11	-2.96	5.41	15.25	124.44	90568
DL_PropInc	4.94	32.18	-637.47	-38.67	5.33	46.93	657.68	90068
DL_FarmPropInc	1.84	93.11	-949.66	-141.22	2.86	140.05	870.62	68110
DL_NonFarmPropInc	5.35	14.02	-288.79	-13.98	5.65	23.29	413.44	90527
PopK	108.44	334.50	0.20	3.15	28.05	477.47	10170.29	92738

Table 6: Summary statistics.

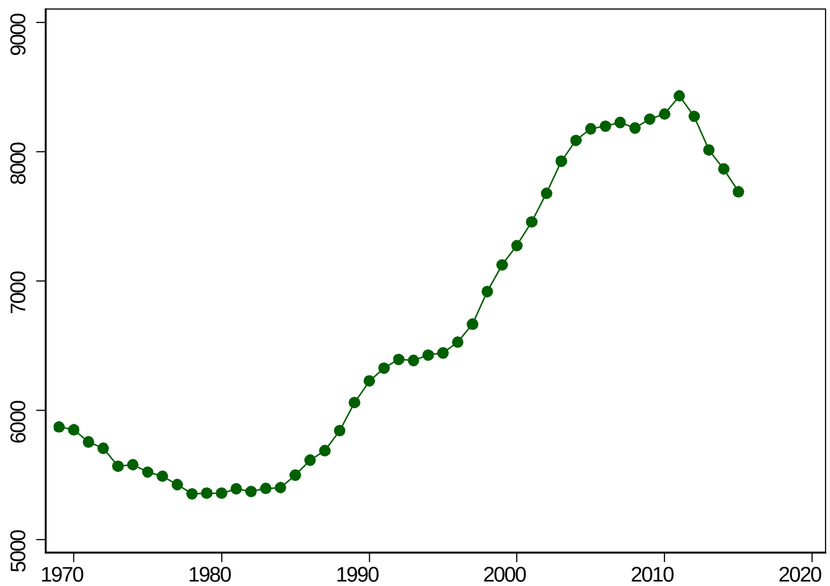


Figure 13: The figure plots the number of weather stations that are used each year in our calculations of county-specific weather.

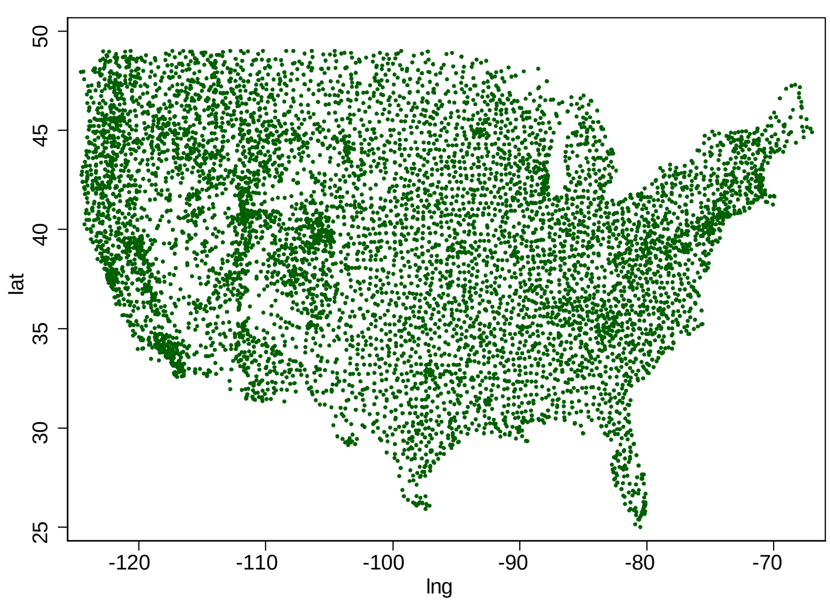


Figure 14: The figure plots the locations of weather stations that are used in 2000 in our calculations of county-specific weather.

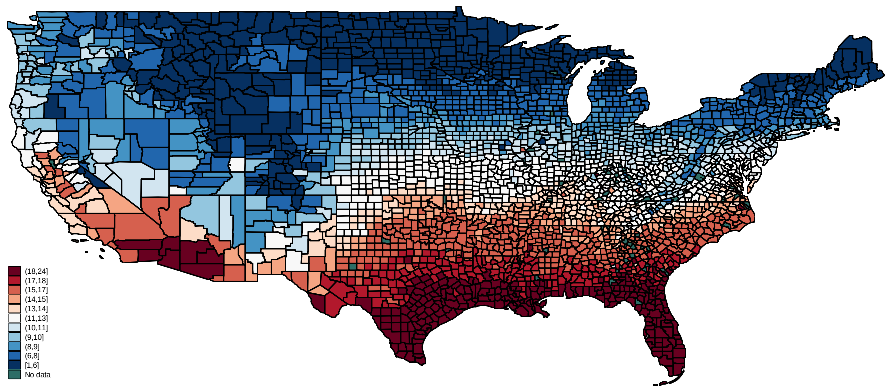


Figure 15: Average annual temperature by county over the period ???.

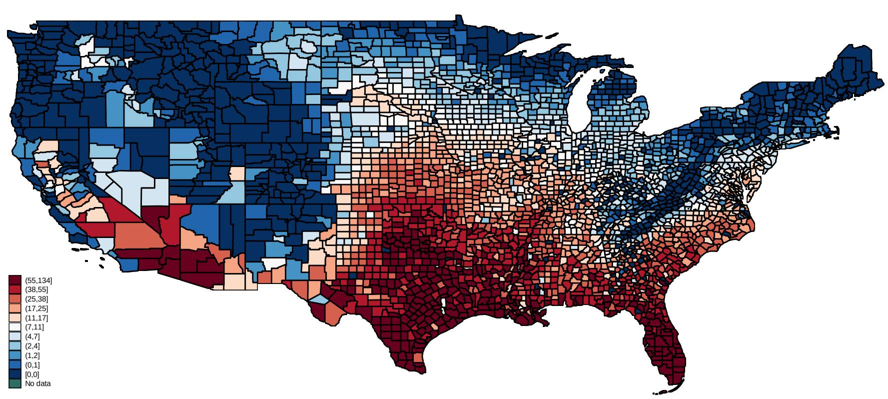


Figure 16: Average number of "hot days" per county over the period ???. A hot day is defined as a day with average temperature above XXX C.

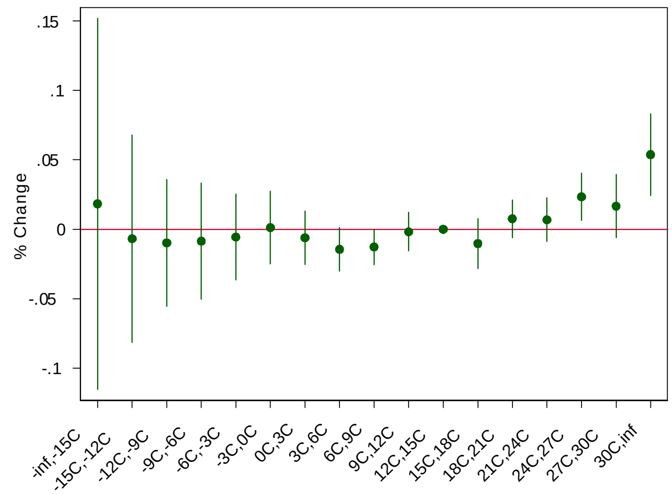
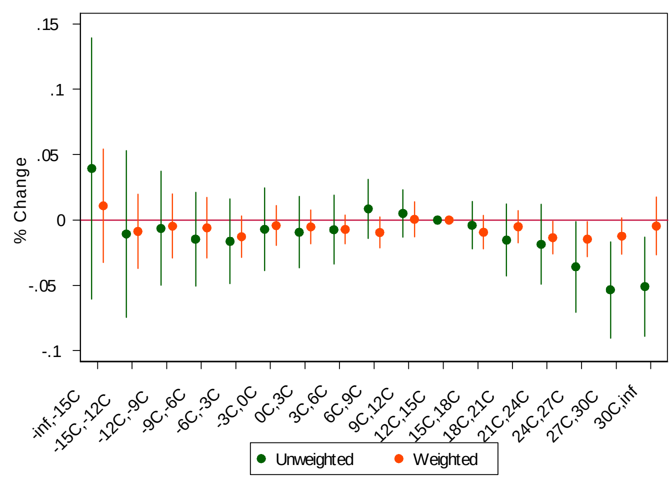


Figure 17: The green circles denote estimates of β_k^{lag} in equation (12), and the bars reflect the associated +/- 2 standard error bands.



8.2 Robustness

We now explore

The specification is:

$$\Delta \log Y_{i,t} = \alpha_i + \delta_t + \sum_{k=1}^{K} \beta_k Bin_{k,i,t} + \sum_{k=1}^{K} \beta_k^{lag} Bin_{k,i,t-1} + \varepsilon_{i,t}, \tag{10}$$

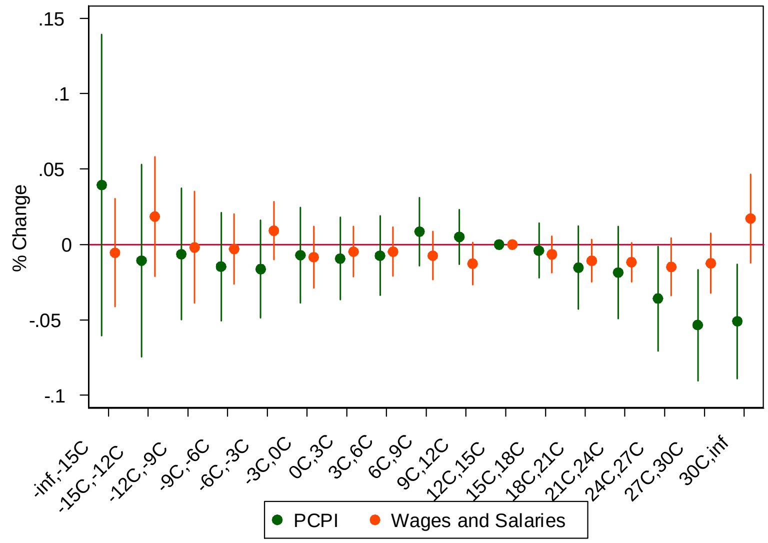
Specification with change in bins — TO BE ADDED

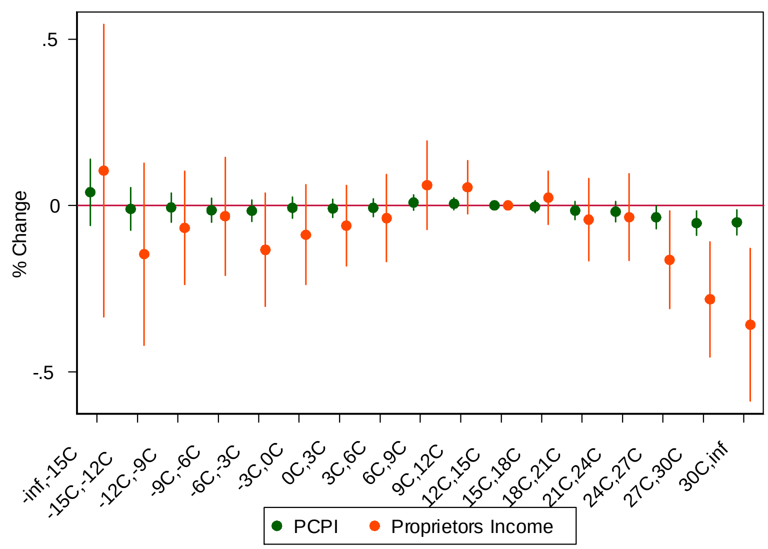
Weighted regressions

Figure presents the results of the same specification as in the paper, but when counties are weighted according to their population. The estimated effects are significantly smaller. Hence, the results appear to be driven by small, rural counties.

	Population Weighted	No Time FE	Bins First Difference	Lagged Current Coefs	Lagged Lagged Coefs	With PRCP Controls
-15C or less	0.0109	0.113	-0.0274	0.0344	0.0268	0.0403
	(0.53)	(1.96)	(-0.40)	(0.74)	(0.43)	(0.90)
-15C,-12C	-0.00866	0.0273	-0.000443	-0.0112	0.00115	-0.00953
	(-0.82)	(0.51)	(-0.01)	(-0.39)	(0.03)	(-0.34)
-12C,-9C	-0.00464	0.0268	0.00570	0.00232	-0.00492	-0.00500
	(-0.35)	(0.66)	(0.18)	(0.08)	(-0.22)	(-0.16)
-9C,-6C	-0.00591	-0.0171	0.00586	-0.00909	-0.00655	-0.0133
	(-0.56)	(-0.52)	(0.27)	(-0.48)	(-0.32)	(-0.75)
-6C,-3C	-0.0127	-0.0165	0.00562	-0.00963	-0.00202	-0.0153
	(-2.00)	(-0.58)	(0.27)	(-0.59)	(-0.11)	(-1.03)
-3C,0C	-0.00417	0.00936	-0.00167	-0.00369	0.00577	-0.00655
	(-0.65)	(0.32)	(-0.10)	(-0.22)	(0.36)	(-0.39)
0C,3C	-0.00519	-0.00700	0.00890	-0.00843	-0.00357	-0.00871
	(-0.97)	(-0.25)	(0.46)	(-0.52)	(-0.26)	(-0.55)
3C,6C	-0.00713	-0.0123	0.0139	-0.00515	-0.0104	-0.00705
	(-1.38)	(-0.54)	(0.99)	(-0.42)	(-0.96)	(-0.54)
6C,9C	-0.00949	0.00482	0.0112	0.00832	-0.0104	0.00886
	(-1.34)	(0.25)	(0.75)	(0.77)	(-0.89)	(0.76)
9C,12C	0.000599	0.0112	-0.00272	0.00207	0.00359	0.00524
	(0.13)	(0.90)	(-0.20)	(0.23)	(0.36)	(0.62)
15C,18C	-0.00931	-0.00242	0.000935	-0.00719	-0.00353	-0.00384
	(-1.64)	(-0.20)	(0.05)	(-0.97)	(-0.31)	(-0.48)
18C,21C	-0.00505	-0.0109	-0.0185	-0.0210	0.0153	-0.0156
	(-0.99)	(-0.56)	(-1.04)	(-1.36)	(1.06)	(-1.05)
21C,24C	-0.0135**	-0.00437	-0.0174	-0.0242	0.0164	-0.0190
	(-2.76)	(-0.22)	(-1.04)	(-1.55)	(1.15)	(-1.25)
24C,27C	-0.0146*	-0.0157	-0.0351	-0.0419*	0.0329*	-0.0363
	(-2.25)	(-0.52)	(-1.78)	(-2.10)	(2.08)	(-1.90)
27C,30C	-0.0123	-0.0625*	-0.0266	-0.0609**	0.0241	-0.0543**
	(-1.57)	(-2.16)	(-1.31)	(-2.81)	(1.46)	(-2.73)
30C or more	-0.00457	-0.0527	-0.0621*	-0.0633*	0.0598**	-0.0525*
	(-0.47)	(-1.96)	(-2.57)	(-2.53)	(2.94)	(-2.30)
N	90529	90529	80587	80587	80587	90529

Table 7: Estimates of the baseline specification for different types of income. Each column refers to a different outcome variable. All regressions include county and time fixed effects. Standard errros clustered by year. Stars indicate statistical significance at the 10 percent (*), 5 percent (**) and 1 percent (***) level.



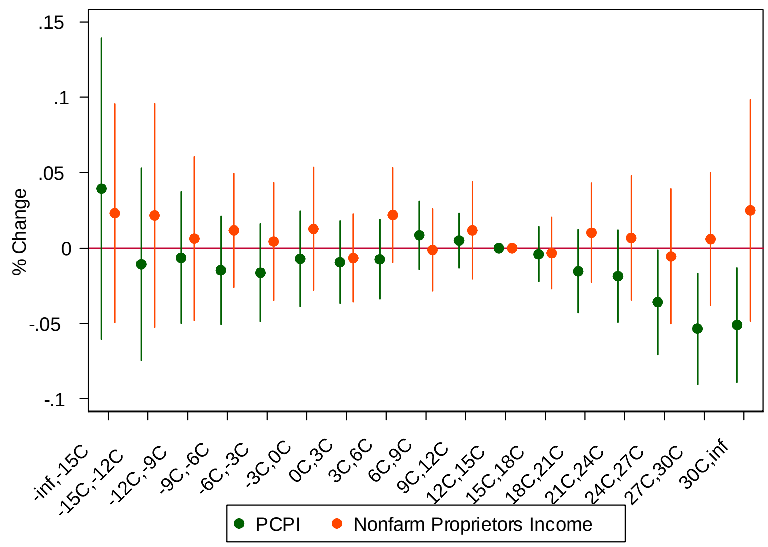


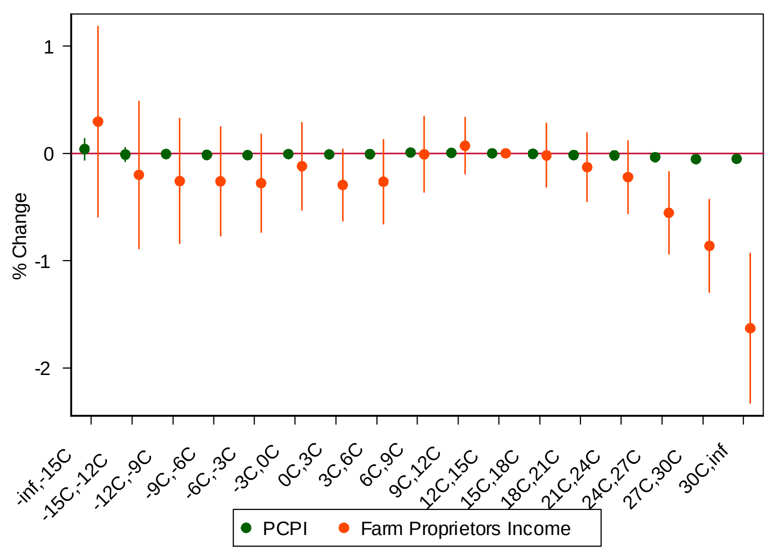
8.2.1 Types of income

The specification is

$$\Delta \log Z_{i,t} = \alpha_i + \delta_t + \sum_{k=1}^{K} \beta_k Bin_{k,i,t} + \varepsilon_{i,t}, \tag{11}$$

where we now use different outcome variables for Z so as to measure the effect of weather on each type of income: (i) wages and salaries (Figure), (ii) proprietor income (Figure), (iii) nonfarm proprietor income (Figure), and (iv) farm proprietor income (Figure).


.15
.1
.05
0
-.05
-.1
% Change
-inf,-15C
-15C,-12C
-12C,-9C
-9C,-6C
-6C,-3C
-3C,0C
0C,3C
3C,6C
6C,9C
9C,12C
12C,15C
15C,18C
18C,21C
21C,24C
24C,27C
27C,30C
30C,inf
PCPI
Nonfarm Proprietors Income


1
0
-1
-2
% Change
-inf,-15C
-15C,-12C
-12C,-9C
-9C,-6C
-6C,-3C
-3C,0C
0C,3C
3C,6C
6C,9C
9C,12C
12C,15C
15C,18C
18C,21C
21C,24C
24C,27C
27C,30C
30C,inf
PCPI
Farm Proprietors Income

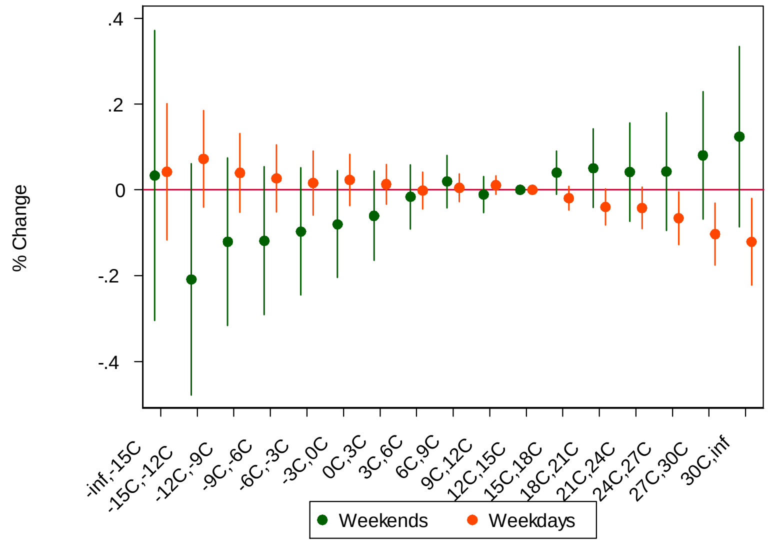


Figure 18: The green circles denote estimates of β_k^{WE} and the red circles denote estimates of β_k^{WDD} in equation (12), and the bars reflect the associated +/- 2 standard error bands.

8.2.2 Weekends vs. Weekdays

The specification is:

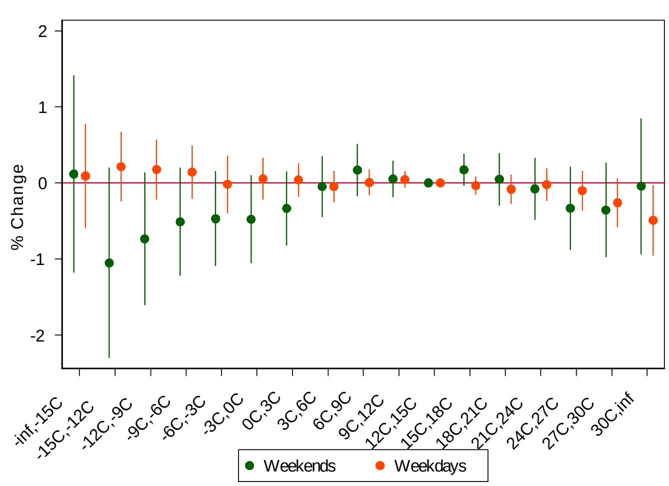
$$\begin{aligned} \Delta \log Y_{i,t} &= \alpha_i + \delta_t + \sum_{k=1}^{K} \beta_k^{WD} Bin_{k,i,t}^{WD} + \sum_{k=1}^{K} \beta_k^{WE} Bin_{k,i,t}^{WE} + \varepsilon_{i,t} \\ Bin_{k,i,t}^{WD} &= \#\text{ of weekdays in bin } k \text{ in county } i \text{ year } t \\ Bin_{k,i,t}^{WE} &= \#\text{ of weekend days in bin } k \text{ in county } i \text{ year } t \end{aligned} \tag{12}$$

The results are shown in Figure 18 and in the first column of Table 8.2.2.

Similar to DH, we observe that the effect of hot days is concentrated on the weekdays. There is a

Weekends vs. Weekdays: Proprietor Income

Weekend vs. Weekdays: Wages and Salaries

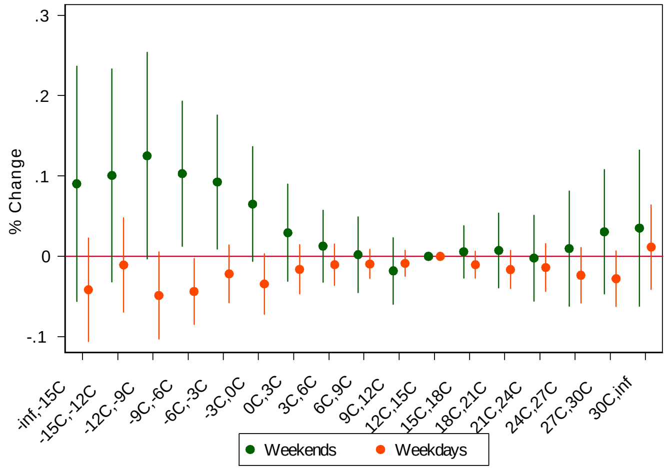


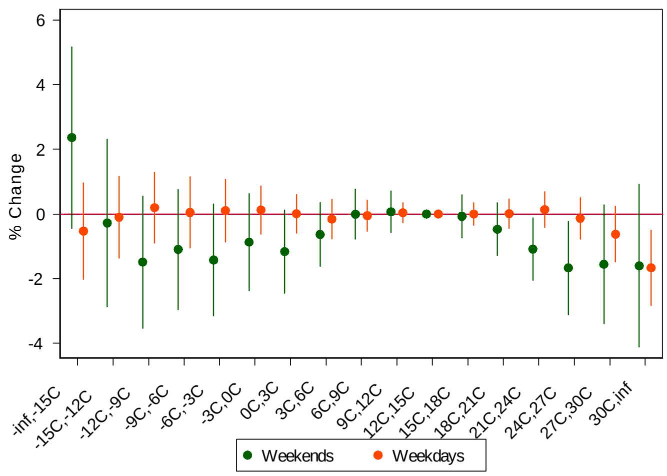
	Income	Wage	Transf.	Div.Int.	Nonfarm	Farm
-15C or less	0.0302	-0.00541	-0.00215	-0.0355	0.0824	-0.441
	(0.61)	(-0.30)	(-0.12)	(-1.51)	(1.21)	(-0.88)
-15C,-12C	-0.00312	0.0186	-0.0108	0.0151	-0.0489	-1.186*
	(-0.09)	(0.94)	(-0.50)	(0.64)	(-0.67)	(-2.37)
-12C,-9C	-0.0102	-0.00191	-0.0114	-0.00282	0.0416	-0.901*
	(-0.46)	(-0.10)	(-0.66)	(-0.13)	(0.94)	(-2.28)
-9C,-6C	-0.0170	-0.00293	-0.0182	-0.0140	0.0244	-0.695*
	(-0.95)	(-0.25)	(-1.33)	(-0.84)	(0.56)	(-2.18)
-6C,-3C	-0.0197	0.00917	-0.00404	-0.0175	-0.00397	-0.766*
	(-1.22)	(0.97)	(-0.32)	(-1.26)	(-0.12)	(-2.30)
-3C,0C	-0.0105	-0.00837	-0.00414	-0.00176	0.0152	-0.882**
	(-0.64)	(-0.82)	(-0.40)	(-0.14)	(0.37)	(-3.00)
0C,3C	-0.0114	-0.00474	-0.00169	-0.0184	-0.0168	-0.823*
	(-0.82)	(-0.57)	(-0.20)	(-1.65)	(-0.71)	(-2.24)
3C,6C	-0.00912	-0.00472	-0.00233	-0.0170	-0.00629	-0.360
	(-0.70)	(-0.59)	(-0.28)	(-1.52)	(-0.21)	(-1.01)
6C,9C	0.00651	-0.00739	0.00313	-0.0137	-0.00659	-0.0558
	(0.59)	(-0.93)	(0.52)	(-1.24)	(-0.19)	(-0.15)
9C,12C	0.00192	-0.0126	0.00515	-0.0101	0.0152	-0.210
	(0.21)	(-1.81)	(1.03)	(-1.09)	(0.49)	(-0.69)
15C,18C	-0.00687	-0.00647	-0.000331	-0.0164	-0.00833	-0.227
	(-0.73)	(-1.09)	(-0.07)	(-1.85)	(-0.26)	(-0.68)
18C,21C	-0.0169	-0.0108	-0.00155	-0.0192	-0.0432	-0.681
	(-1.16)	(-1.54)	(-0.26)	(-1.67)	(-1.15)	(-1.74)
21C,24C	-0.0214	-0.0117	0.00245	-0.0254	-0.00338	-0.898*
	(-1.30)	(-1.81)	(0.36)	(-1.85)	(-0.10)	(-2.53)
24C,27C	-0.0366	-0.0149	0.00239	-0.0268	-0.000767	-1.131*
	(-2.00)	(-1.56)	(0.34)	(-1.69)	(-0.02)	(-2.21)
27C,30C	-0.0562**	-0.0124	-0.00793	-0.0199	-0.0898	-0.322
	(-3.03)	(-1.25)	(-1.17)	(-1.31)	(-0.95)	(-0.29)
30C or more	-0.0485*	0.0172	-0.0106	0.00640	-0.363***	-6.532*
	(-2.56)	(1.19)	(-1.01)	(0.28)	(-3.53)	(-2.35)
N	90529	90529	90529	90529	18127	12650

Table 8: Estimates of the baseline specification for different types of income. Each column refers to a different outcome variable. All regressions include county and time fixed effects. Standard errros clustered by year. Stars indicate statistical significance at the 10 percent (*), 5 percent (**) and 1 percent (***) level.

	PIPC WD	PIPC – Weekdays	Wages - Weekdays	Wages - Weekends	NFARM WD	NFARM WE
-15C or less	0.0335	0.0422	0.0903	-0.0415	2.365	-0.530
	(0.22)	(0.58)	(1.09)	(-1.41)	(1.75)	(-0.79)
-15C,-12C	-0.209	0.0722	0.101	-0.0107	-0.276	-0.103
	(-1.73)	(1.49)	(1.38)	(-0.36)	(-0.20)	(-0.18)
-12C,-9C	-0.121	0.0397	0.125	-0.0486	-1.488	0.196
	(-1.35)	(0.81)	(1.91)	(-1.80)	(-1.47)	(0.39)
-9C,-6C	-0.119	0.0268	0.103*	-0.0436*	-1.097	0.0435
	(-1.47)	(0.74)	(2.07)	(-2.30)	(-1.15)	(0.08)
-6C,-3C	-0.0971	0.0161	0.0926*	-0.0217	-1.426	0.104
	(-1.40)	(0.44)	(2.36)	(-1.05)	(-1.62)	(0.22)
-3C,0C	-0.0802	0.0232	0.0651	-0.0343	-0.871	0.122
	(-1.40)	(0.77)	(1.81)	(-1.84)	(-1.13)	(0.34)
0C,3C	-0.0605	0.0130	0.0295	-0.0162	-1.164	0.00732
	(-1.22)	(0.54)	(0.96)	(-1.04)	(-1.73)	(0.03)
3C,6C	-0.0162	-0.00173	0.0127	-0.0104	-0.634	-0.157
	(-0.47)	(-0.08)	(0.59)	(-0.79)	(-1.29)	(-0.54)
6C,9C	0.0197	0.00470	0.00208	-0.00948	-0.00687	-0.0530
	(0.68)	(0.29)	(0.10)	(-1.16)	(-0.02)	(-0.24)
9C,12C	-0.0110	0.0109	-0.0180	-0.00870	0.0659	0.0404
	(-0.54)	(0.93)	(-0.95)	(-1.12)	(0.22)	(0.27)
15C,18C	0.0402	-0.0195	0.00578	-0.0104	-0.0722	-0.000592
	(1.59)	(-1.33)	(0.34)	(-1.58)	(-0.22)	(-0.00)
18C,21C	0.0505	-0.0399	0.00737	-0.0164	-0.474	0.0121
	(1.18)	(-1.60)	(0.29)	(-1.48)	(-1.13)	(0.05)
21C,24C	0.0416	-0.0422	-0.00211	-0.0139	-1.089*	0.136
	(0.77)	(-1.54)	(-0.07)	(-1.02)	(-2.11)	(0.48)
24C,27C	0.0427	-0.0659	0.00968	-0.0234	-1.669*	-0.135
	(0.68)	(-1.96)	(0.27)	(-1.51)	(-2.22)	(-0.44)
27C,30C	0.0805	-0.103*	0.0306	-0.0277	-1.560	-0.627
	(1.17)	(-2.58)	(0.73)	(-1.76)	(-1.74)	(-1.50)
30C or more	0.124	-0.121*	0.0352	0.0116	-1.606	-1.666**
	(1.25)	(-2.10)	(0.81)	(0.45)	(-1.37)	(-3.30)
N	90529	90529	90529	90529	68059	68059

Table 9: Estimates of the baseline specification for different types of income. Each column refers to a different outcome variable. All regressions include county and time fixed effects. Standard errros clustered by year. Stars indicate statistical significance at the 10 percent (*), 5 percent (**) and 1 percent (***) level.



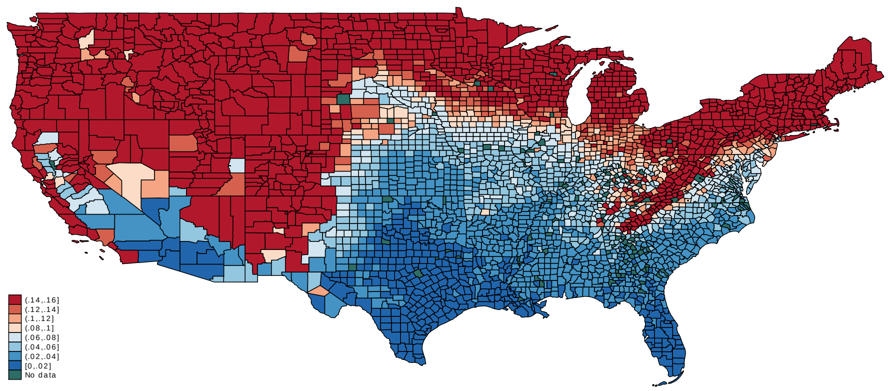


Weekend vs. Weekdays: Farm Proprietor Income

8.3 Additional structural model results

8.3.1 Estimated Sensitivity to Temperature

Figure 8.3.1 depicts the estimated sensitivity to hot days in the current environment. Figure 8.3.1 shows how the model projects these sensitivities will change given climate change, after adaptation has taken place.



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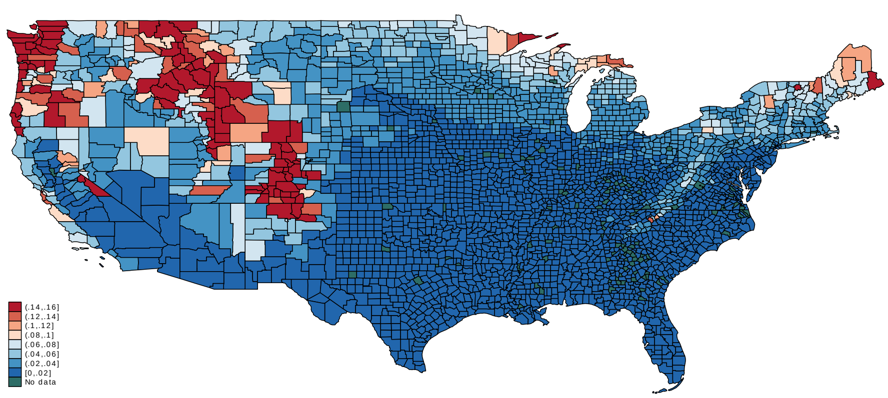

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