Weather Shocks and Climate Change*

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– preliminary and incomplete —

Abstract

Weather shocks, i.e. deviations of temperature from historical values, have significant effects on economic activity, even in developed economies such as the United States. This has been interpreted as evidence of limits to adaptation. We document a large heterogeneity in the sensitivity of economic activity to weather shocks across regions within the US, and show that this heterogeneity is largely explained by differences in average temperature. This leads us to interpret these differences as the result of adaptation choices that regions make given their specific climate. We use the reduced form estimates to identify a simple structural model of adaptation. Our model estimates how much region has adapted already, and can also predict how much each would adapt after climate change. The size and distribution of losses from climate change vary substantially once adaptation is taken into account – both in the case where adaptation stays as currently estimated, or changes after climate change.

JEL codes: E23,O4,Q5,R13.

Keywords: climate change, adaptation, weather effects.

1 Introduction

Climatologists project a significant increase in global temperature over the next century, leading to multiple effects on human communities. A substantial recent literature establishes that high temperatures lead to low output.[1] This body of research controls for a region's average temperature by using panel data with regional fixed effects and can therefore identify economic sensitivity to "weather shocks", defined as temperature deviations from normal values. 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. Some studies [2] build on these findings to estimate the impact of global warming by

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[1] See Dell, Jones and Olken (2012), Burke et al. (2015), Deriyugina and Hsiang (2014), Colacito, Hoffman and Phan (2015).

[2] For a recent elaborate example, see Hsiang et al. (2016)

interpreting climate change as a permanent weather shock. One well-known underlying assumption is that there is no adaptation to the change in climate. Another less obvious assumption is that the impact of weather shocks is the same in all US regions.

Our paper builds on this approach by using evidence of heterogenous sensitivity to weather shocks to measure the cost of adaptation and its role in the eventual economic impact of climate change. Our first contribution is to document a large heterogeneity in sensitivity to weather shock across US counties. Places that are ordinarily warm, such as the South, are largely unaffected by high temperature realizations, while colder regions in the North exhibit larger sensitivities. In the language of the treatment effect literature, previous research has identified correctly an economically and statistically significant "average treatement effect" but has not focused on the heterogeneity in this treatment effect. We show that the variable that explains the best the sensitivity heterogeneity is simply local climate - e.g. the average temperature.

We interpret this heterogeneity as a consequence of adaptation. Households and firms who operate in the South are aware of its historical climate and, consequently, have made decisions to reduce the effect of hot days. The North has not faced similar conditions, and thus has not made similar decisions, even though the same technologies are available. The North has not faced similar conditions, and thus has not made similar decisions. Presumably, the cost of adaptation cannot be justified given the cooler northern climate.

Our second contribution, is to use the cross-section of sensitivies to weather shocks to infer the cost of adaptation. To do so, we estimate a structural model incoporating (i) weather variation, (ii) economic sensitivity to weather shocks, and (iii) a margin of adaptation. Each region is allowed to decide how much to invest in adaptation, which involves a cost but reduces sensitivity to days with high temperature. We estimate key parameters of the model to fit the evidence that: (i) the average US county is sensitive to heat and (ii) counties with higher average temperature have lower sensitivity.[3]

We then simulate the effect of climate change using our structural model. We find it useful to compare three different assumptions about adaptation, which correspond respectively to constant adaptation across time and space, constant adaptation across time and varying across space, and varying adaptation across time and space. We call these the no adaptation, fixed adaptation, and endogenous adaptation cases.

Our counterfactual analysis leads us to four main conclusions. Unsuprisingly, allowing endogenous adaptation results in lower economic losses than if adaptation is fixed. For instance, we estimate that a 5.1C warming would lead to losses of -1.71% if counties adapt further in response to the warming, but -4.18% if they do not.

Second, we find that the dispersion in losses (across regions) is much smaller once adaptation is taken into account. The standard deviation across counties of losses is 0.51% with adaptation and 2.22% without. This is because the same counties that have the most to lose from climate change benefit the most from being able to adjust in the future.

Third, merely taking into account currently observed adaptation, i.e. varying adaptation across space

[3]The underlying intuition is if global warming means Chicago's future climate climate will become like New Orleans's current climate, New Orleans's current sensitivity is informative of Chicago's future sensitivity.

only, reduces the median and dispersion of losses expected from climate change. The counties projected to see the largest increase in high temperature are currently the least sensitive to these episodes.

Fourth, assumptions about adaptation influence the distribution of losses, and in particular who loses most. The South is the most affected in the no adaptation case, but the Midwest and Northeast are most affected in the fixed and endogenous adaptation cases.

There are obviously a number of caveats to our study, which we discuss in section 4.

The rest of the paper is organized as follows. The remainder of the introduction discusses related literature. Section 2 provides evidence about the effect of weather shocks in the US, and documents the heterogeneity in sensitivities across US regions. Section 3 presents and estimates our simple structural model. Section 4 discusses the effect of climate change in our model. Section 5 presents various robustness exercises and extensions, and Section 6 concludes.

1.1 Literature review

The growing literature on the economics of climate change, pioneered by Nordhaus (e.g. 1994, 2000), focuses primarily on the economy's effect on the climate and how policy should address the central pollution externality. Two recent prominent studies in this field are Acemoglu et al. (2016) and Krusell et al. (2016). In contrast, our paper focuses solely on the propagation from climate to economy. There is a substantive empirical literature on the effect of weather fluctuations on the economy. As noted above, and as reviewed in Dell, Olken, and Jones (2014), these studies use regional fixed effects to identify the economic impact of "weather shocks". Dell, Olken and Jones (2012) offers cross-country annual panel data analysis demonstrating that poor countries' GDPs are affected negatively by higher than average temperature realizations. Perhaps surprisingly, this effect is neither driven purely by agriculture nor made up fully over following years. Extending this work, Burke et al. (2015) demonstrate that the effect of temperature on GDP is nonlinear. This non-linearity evidentlly holds even in rich countries, which one might assume immune to most weather variation. Deryugina and Hsiang (2014) provide similar evidence of the nonlinearity in the United States using county-year data. Colacito, Hoffman and Phan (2015) also offer supporting evidene that high temperature generate low output in the US using state level GDP data.

Various studies have examined the effect of weather on other features of economic activity, such as agriculture (Greenstone and Deschenes, 2013) or hours worked (Graff, Zidin, and Neidell, 2014). Other studies have demonstrated a short-run effect of weather on economic indicators in the United States (Boldin and Wright (2015); Bloesch and Gourio (2015); Foote (2015)).

The margins of adaptation to climate change have also been studied in several papers. Some papers note that the short-run effect is an upper bound on the effects of weather (e.g., Greenstone and Deschenes (2013)), while others explicitly study various mechanisms for adaptation. Greenstone et al. (2015) demonstrate that mortality has become less sensitive to hot days over time and link this to the development of AC technology.

2 Evidence

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

2.1 Data

Our dataset is created by combining income and weather data at the county level and annual frequency. The income statistics are compiled from the Bureau of Economic Analysis (BEA) and provide a measure of a county's total personal income per capita as well as its breakdown.[4] These series are available at the annual frequency since 1969. We construct our weather statistics using the US-HCN (historical climate network) database, provided by the National Centers for Environmental Information (NCEI, formerly NCDC). US-HCN collects daily measures of temperature,[5] precipitation, and snowfall at the weather station level, which we aggregate to the county-level by taking a simple average of all weather stations located in a county.[6] We merge county-year income and weather statistics to produce a unbalanced sample of 2,901 counties over the period 1969-2015. Table 11 in the appendix presents summary statistics of 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 nominal income in county i in year t, α_i is a county fixed effect, δ_t a time fixed effect, and $Bin_{k,i,t}$ is the number of days in year t in county i where temperature falls in bin $k = 1...K$. The central bin (12 °C-15 °C) is omitted, providing a reference by which temperature deviations are evaluated. Following Deryugina and Hsiang (2014) we use $K = 17$ bins to capture the possibly nonlinear effects of temperature on income.[7] This specification is appealing because the distribution of days across bins varies from year to year due to random weather fluctuations. With the

[4] Income is broken down into wages, wage supplements, transfers, proprietor income, and capital income (dividends, interest and rent).

[5] Temperature is defined as the average of the maximum and minimum temperatures of that day.

[6] In untabulated results, we used an alternative approach to measure county weather. 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.

[7] Our specification differs from that paper only in that we use the log change of income per capita as the dependent variable; in contrast their paper uses the log (level) of income per capita, and adds 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. The standard errors are almost identical if one clusters by year simply, or by county-year.

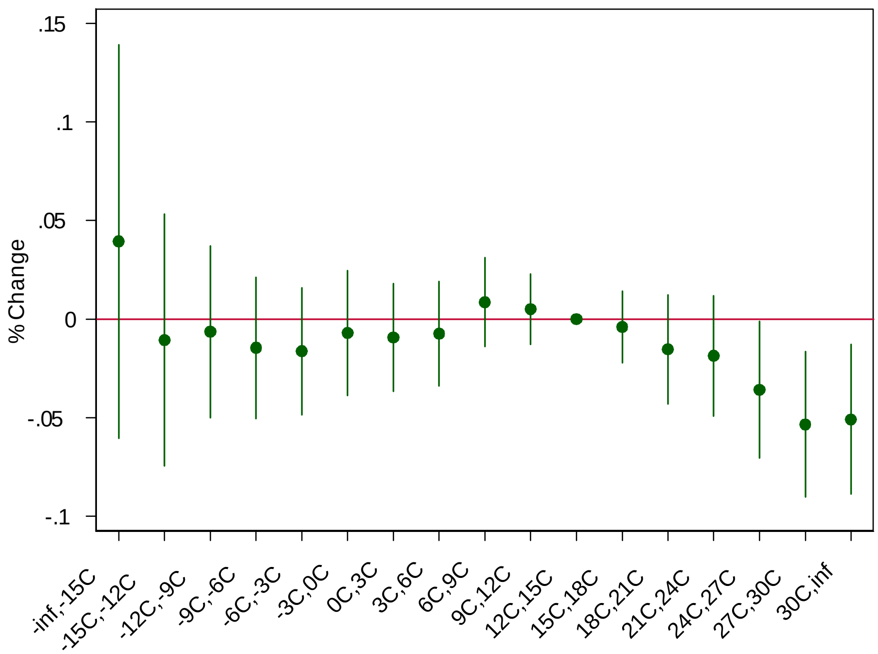

Figure 1: The circles denote estimates of β_k in equation (1), and the bars reflect the associated plus or minus two standard error bands. β_k is the marginal effect of an additional day in the relevant temperature bin (relative to a day with average temperature between 12 °C and 15 °C) on annual income growth.

inclusion of county fixed effects we are effectively comparing the growth rate of income in a county in two years that differ in their composition of days by temperature.

Consistent with Deryugina and Hsiang (2014), we find that the marginal day above 27 °C, or perhaps even 24 °C, affects income growth negatively. Figure 1 depicts the results, and Table 1 presents coefficient estimates and the associated standard errors in Column 1. An additional day in the hottest bin reduces annual income by about 0.05%, relative to the omitted reference bin (12 °C-15 °C). If income is generated linearly across the year, one day corresponds only to 1/365=0.27% of annual income, and then the reduction of daily income due to a 0.05% decrease in annual income amounts to a 18% decline in daily income (0.05/0.27), which is a large effect.[8]

The appendix reports several variants and robustness checks on this basic result. We show that (1) the effects are essentially reversed the following year, (2) the results are concentrated on weekdays, (3) the results are concentrated on farm proprietary income.[9]

[8] 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 production greater than a 100% for a hot day.

[9] 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, wages and salaries actually increase with temperature on weekends.

	Baseline	Quintile 1	Quintile 2	Quintile 3	Quintile 4	Quintile 5
-15 °C 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)
-15 °C,-12 °C	-0.0107	-0.0792*	-0.0280	0.0659	0.188	-0.604*
	(-0.34)	(-2.37)	(-0.48)	(1.04)	(1.55)	(-2.49)
-12 °C,-9 °C	-0.00638	-0.0629*	-0.00976	0.0620	-0.0166	0.430*
	(-0.29)	(-2.02)	(-0.27)	(1.15)	(-0.22)	(2.26)
-9 °C,-6 °C	-0.0146	-0.0391	-0.0429	0.00257	-0.0121	0.142
	(-0.82)	(-1.62)	(-1.78)	(0.06)	(-0.33)	(1.26)
-6 °C,-3 °C	-0.0163	-0.0625**	-0.0179	-0.00763	-0.0136	-0.0909
	(-1.01)	(-2.84)	(-0.75)	(-0.24)	(-0.44)	(-1.54)
-3 °C,0 °C	-0.00704	-0.0586*	-0.0223	0.0143	0.0294	-0.0435
	(-0.45)	(-2.61)	(-0.92)	(0.47)	(1.30)	(-1.62)
0 °C,3 °C	-0.00932	-0.0435	-0.0197	0.00331	0.0170	0.0167
	(-0.69)	(-1.89)	(-0.97)	(0.12)	(0.95)	(0.93)
3 °C,6 °C	-0.00739	-0.0226	-0.00585	-0.0113	0.00342	0.00822
	(-0.56)	(-1.04)	(-0.26)	(-0.39)	(0.18)	(0.42)
6 °C,9 °C	0.00859	0.00836	0.00544	0.0213	-0.0136	0.00189
	(0.77)	(0.42)	(0.22)	(0.73)	(-1.09)	(0.12)
9 °C,12 °C	0.00505	0.00423	-0.0123	0.0127	0.00437	-0.00281
	(0.57)	(0.20)	(-0.66)	(0.55)	(0.33)	(-0.25)
15 °C,18 °C	-0.00400	-0.0116	0.0202	-0.00446	-0.00703	-0.00469
	(-0.44)	(-0.57)	(1.14)	(-0.25)	(-0.44)	(-0.34)
18 °C,21 °C	-0.0153	-0.0656*	-0.0254	0.00692	-0.00188	0.0109
	(-1.12)	(-2.49)	(-1.11)	(0.28)	(-0.12)	(0.70)
21 °C,24 °C	-0.0186	-0.0401	-0.0366	-0.0238	0.000826	0.00653
	(-1.23)	(-1.28)	(-1.61)	(-0.86)	(0.05)	(0.54)
24 °C,27 °C	-0.0358*	-0.0781	0.00268	0.00321	-0.00210	0.0132
	(-2.08)	(-1.77)	(0.09)	(0.13)	(-0.12)	(0.95)
27 °C,30 °C	-0.0534**	-0.277*	-0.160**	-0.0518	-0.0222	0.00388
	(-2.92)	(-2.10)	(-2.79)	(-1.41)	(-1.22)	(0.29)
30 °C 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 (Equation 1) for the entire sample (Column 1) and for each quintile of counties, sorted by their average temperature (Columns 2-6). All regressions include county and time fixed effects. Standard errors clustered by year. Stars indicate statistical significance at the 10 percent (*), 5 percent (**) and 1 percent (***) level.

2.3 Heterogeneity in Sensitivity

We proceed to document the heterogeneity across regions in sensitivity to temperature. The sensitivity of income to hot days is smaller in hotter places. This is true even if we control for other county characteristics. We show this result first using a simple subsample analysis, then a set of richer interaction models, and finally using a random coefficient model.

2.3.1 Subsample analysis

Our subsample analysis approach involves dividing all counties into five quantiles of the average annual temperature, and estimating our baseline regression separately for each quintile. Results are shown in Table 1 and depicted in Figure 2.

The effect of days above 30 °C for counties in the first quintile is around -0.5%. This is imprecisely estimated because these counties have few hot days. In the second quintile the sensitivity is similar but precisely estimated, with a t-stat close to four. In the third quintile, the coefficient is halved, but it remains highly statistically significant. In quintile four, the coefficient drops to -0.01 and is indistinguishable from zero. In quintile five, the point estimate is positive, though not significantly. Economically, the last two quintiles have a fairly precisely estimated sensitivity which is close to zero. The results are similar for the response to the number of days between 27 °C and 30 °C. In that case, the coefficient goes from -0.28, -0.16, -0.05, -0.02, to 0.004. The average treatment effect estimated by the baseline equation (1) hence reflects considerable heterogeneity.

2.3.2 Interaction model

One potential issue with our subsample analysis is that average temperature might be correlated with other characteristics that affect the sensitivity to weather, such as income. The division into quintiles is also arbitrary. These concerns lead us to estimate a model where the coefficients on the temperature bins are allowed to vary with the average temperature of the county, $\overline{T_i}$, as well as 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 L factors that might affect the sensitivity of the county to weather. Our baseline model, Equation (1), is equivalent to Equation (2) if x_{ilt} is a constant. Figure 3 report the marginal effect of a day above 30 °C for four alternative models which differ in the set of variables included in x_{ilt}. In addition to a constant, the top-left panel (A) consider a quadratic model in the average county temperature $\overline{T_i}$, so $x_{ilt} = \{1, \overline{T_i}, \overline{T_i}^2\}$, the top-right panel (B) depicts a cubic model $x_{ilt} = \{1, \overline{T_i}, \overline{T_i}^2, \overline{T_i}^3\}$, the bottom-left panel (C) includes a control for log income and time (to control for trends), $x_{ilt} = \{1, \overline{T_i}, \overline{T_i}^2, t, \log y_{it}\}^2$, and finally the bottom right panel (D) adds to that the average share of farming income in the county $share_i$, so that $x_{ilt} = \{1, \overline{T_i}, \overline{T_i}^2, share_i\}^2$.

Regardless of the exact specification, we observe a large decline in the sensitivity to hot days as the average temperature of the county rises. For the warmest US counties, it is impossible to reject that this effect is (a fairly precisely estimated) zero. Moreover, the effects are fairly similar across specifications.

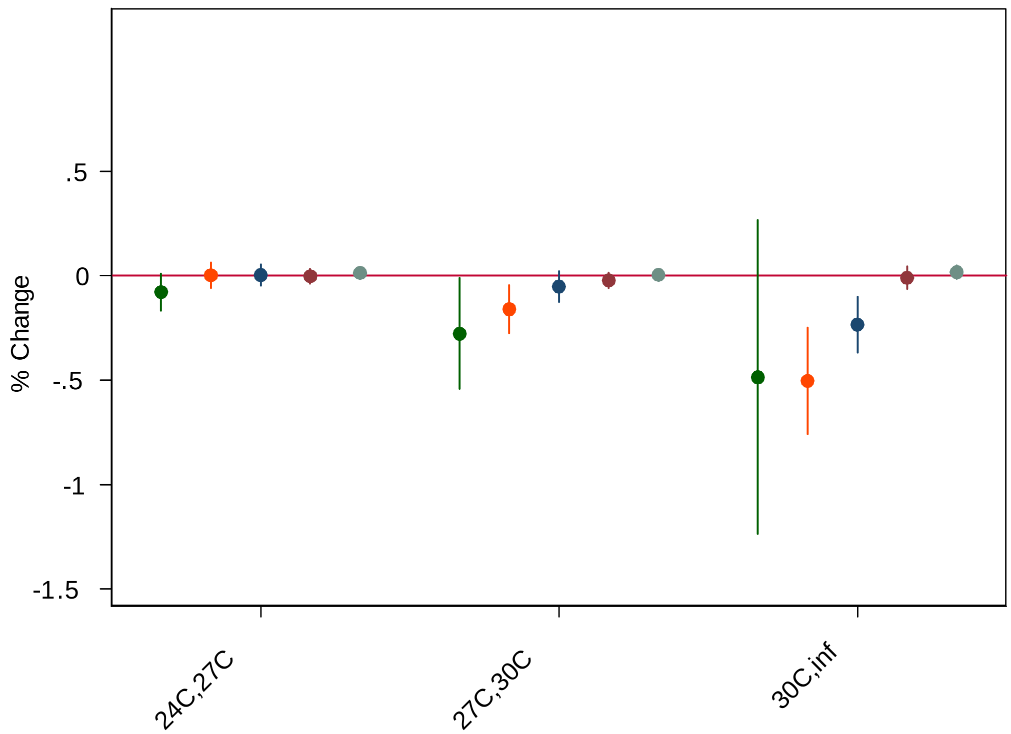

Figure 2: The circles denote estimates of β_k in equation (1) for $k = 15, 16, 17$ (three hottest temperature bins), for each of the five groups of counties (quintiles ordered by average temperature), and the bars reflect the associated +/- 2 standard error bands.

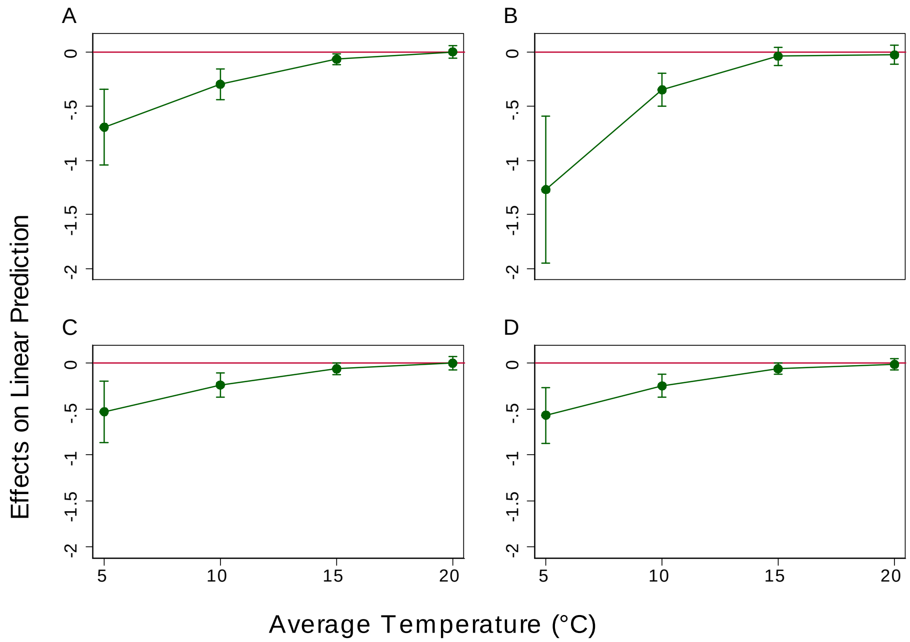

Figure 3: The figure plots the estimated marginal effect of a day with average temperature above 30 °C from model (2), for different values of the average temperature of the county $\overline{T_i}$. (A) Quadratic average temperature model, (B) Cubic average temperature model, (C) Quadratic average temperature with linear trend and log income model, (D) Quadratic average temperature with linear farming share model.

In particular, controlling for income has a small effect on this result. The one specification that is somewhat different is the cubic model,which has larger standard errors, but suggests an even larger sensitivity in cold counties.

2.3.3 Random coefficient model

The results in this section are preliminary. To document the heterogeneity in responses in a less parametric way, we estimate a random coefficient model. We focus on a simple specification that uses only the last bin ($K = 17$ corresponding to days with average temperature above 30 °C):

$$\Delta \log Y_{i,t} = \alpha_i + \delta_t + \beta_{i,K} Bin_{K,i,t} + \varepsilon_{i,t}, \tag{3}$$

where α_i and $\beta_{K,i}$ are both random effects and δ_t is a fixed effect. To enhance statistical power, we pool by state, in effect assuming that the slope coefficient is constant across counties within the same state:

$$\Delta \log Y_{i,t} = \alpha_{s(i)} + \delta_t + \beta_{s(i),K} Bin_{K,i,t} + \varepsilon_{i,t}, \tag{4}$$

where $s(i)$ is the state of county i. This average of the estimated $\beta_{s(i),K}$ has a mean of -0.203 with a standard deviation of this slope across states equal to 0.046. Figure 4 depicts the filtered slopes against

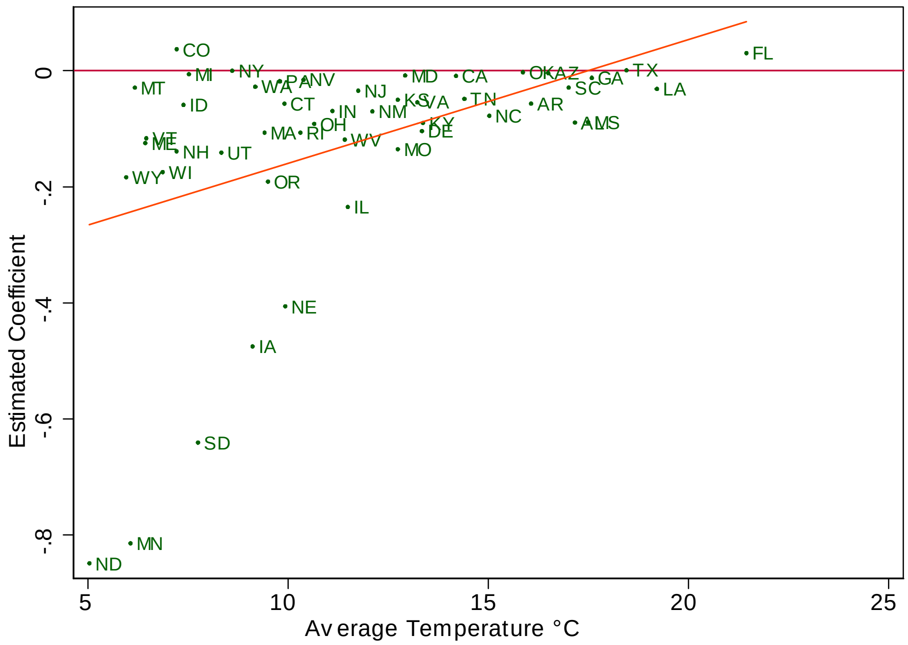

Figure 4: The figure plots the estimates of a random coefficient model from equation (4), pooled by state, against the average temperature of the state, together with a regression line.

the average temperature of the state. Again, we see that cooler states have a larger (in absolute value) sensitivity.

3 Structural Model

This section presents and estimates a structural model of adaptation. We use the model for counterfactual analysis in the next section to study the effect of potential climate change. The model, while highly stylized, captures two key features: (1) the effect of temperature on productivity, and (2) an endogenous adaptation margin whereby counties can invest to reduce their exposure to temperature. In the first subsection, we present the model assumptions and solution. In the second subsection, we estimate the model to replicate some of our empirical results of section 2.

3.1 Model description

The model is 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. Counties are autarkic: there is neither trade nor population migration. For simplicity we assume that the time period is a day. (This simplifies the mapping between the model and the reduced form work.) 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 neither trade and nor capital, the resource constraint of county i reads:

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

The county has a representative household with standard preferences:[10]

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

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

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

This relationship is depicted in figure 5. Here b_0 is the baseline productivity, assumed constant over time and across counties. (Given our empirical approach, which removes county and time fixed effects, this simplification is without loss of generality.) The parameter $\overline{T}$, assumed constant across counties, is the threshold past which productivity starts to fall; and finally $b_1(k)$ is the rate at which productivity falls with each degree above $\overline{T}$. This rate is endogenously chosen as we will explain shortly. In section 5, we consider alternative functional forms.

[10] 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.

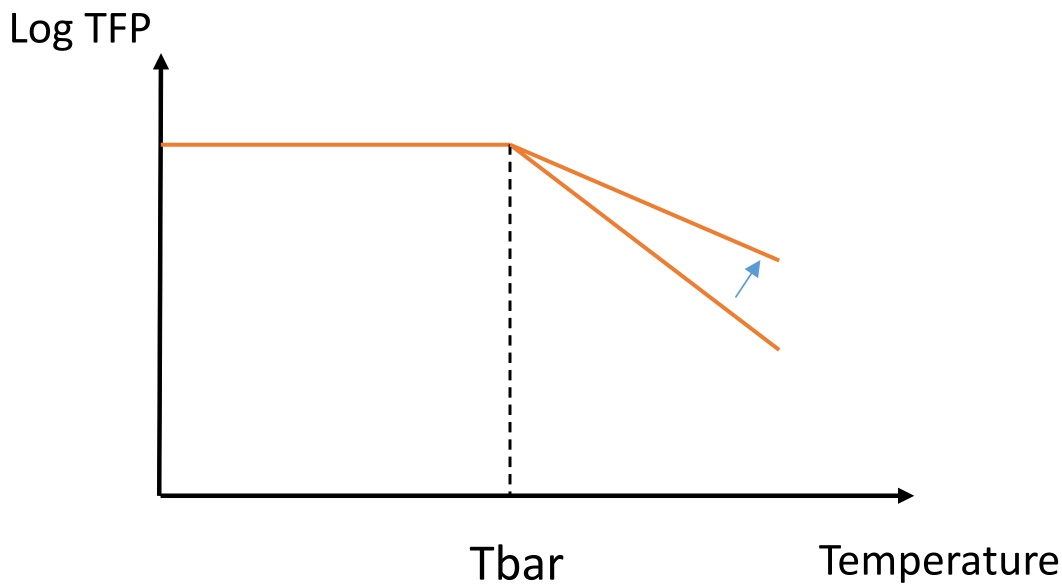

Figure 5: This figure illustrates the relationship between temperature and productivity assumed in our model. The arrow depicts the effect of investment in adaptation.

Temperature T_{it} is assumed to be iid over time[11] and is drawn from a (constant) county-specific cumulative distribution function $F_i(.)$.[12] This temperature distribution is the only exogenous difference across counties in our model, which are assumed to share the same parameters.

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 temperature. The cost k reduces output in all states of nature, 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

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

Importantly, this cost is a once-and-for-all choice, rather than a margin that can be varied instantaneously in response to temperature today. In each county, the representative household makes a choice of adaptation, knowing perfectly the distribution of its future temperature $F_i(.)$.[13]

[11] Of course, the iid assumption for T_{it} is not true at the daily frequency (though it holds approximately at the annual 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.

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

[13] The model can be viewed as a static model, where the choice of adaptation is made before the temperature realizations; or it can be viewed as a dynamic model, where the choice of adaptation is a sunk cost. In this case k is the amortized cost per year of the investment in adaptation, which is made at time 0.

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). Then, we can solve for the optimal level of adaptation. Since counties do not interact, we can solve each county's equilibrium independently.

The first step involves writing the first order condition equating the marginal rate of substitution 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 $C_{it} = (1-k)A_{it}N_{it}^{\alpha}$, leading 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 output is given by

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

This can be conveniently expressed in log as:

$$\log N_{it} = \frac{1-\gamma}{1+\psi+\alpha(\gamma-1)} \log A_{it} + \text{constant}, \tag{5}$$

$$\log Y_{it} = \frac{1+\psi+2\alpha\,(1-\gamma)}{1+\psi+\alpha(\gamma-1)} \log A_{it} + \text{constant}. \tag{6}$$

We can then define the expected utility of a county that has climate F_i and chooses adaptation k as:

$$\begin{aligned} V(k;F_i) &= \max_{N_{it}} E\sum_{t=0}^{\infty}\beta^t\left(\frac{C_{it}^{1-\gamma}}{1-\gamma} - \frac{N_{it}^{1+\psi}}{1+\psi}\right), \\ s.t. &: \quad Y_{it} = A_{it}(k,T_{it})N_{it}^{\alpha} \text{ and } T_{it} \ \rightarrow F_i(.). \end{aligned} \tag{7}$$

This expression 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 (5) 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 $s = 1...S$, allowing us to calculate V 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 find the optimal adaptation choice as

$$k^* = \arg\max_k V(k;F_i). \tag{8}$$

We implement this by a discretization of k, but we consider a grid thin enough that discreteness has no impact on the results.

symbol	value	meaning		s.e.
β	irrelevant	discount factor	preset	n.a.
γ	1	consumption IES	preset	n.a.
ψ	1	labor supply IES	preset	n.a.
α	0.7	labor share	preset	n.a.
$\overline{T}$	26 °C	threshold	preset	n.a.
$\overline{b_1}$	0.208	sensitivity of TFP to T if $T > \overline{T}$	estimated	0.024
θ	131.21	effectiveness of adaptation	estimated	0.176

Table 2: Parameters used in the model.

3.3 Model estimation

Our simple model captures the margin of adaptation which is critical for the economic impact of climate change. The challenge is to estimate the parameters that govern adaptation. Our approach is to 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 approach to choosing parameters is as follows. We preset some parameters based on previous research or commonly agreed macro elasticities. We assume a functional form for the adaptation function:

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

where the parameter $\overline{b_1}$ captures the sensitivity of productivity to temperature above $\overline{T}$ without adaptation ($k = 0$) and the parameter θ measures cost of adaptation.[14] (Section 5 presents results for alternative functional forms.) We then estimate the two critical parameters $\overline{b_1}$ and θ to replicate the regressions of income on number of hot days by quintile.

Specifically, our preset parameters are listed in Table 2. We use standard macro elasticities of one for consumption and leisure. We set the labor share to 0.7 and, based on the evidence above, set the threshold temperature $\overline{T}$ to 26C. To estimate $\overline{b_1}$ and θ, we use indirect inference (Gourieroux, Monfort and Renault (1993), Smith (1993)). Our target moments in the data are obtained as follows: we sort counties into five quintiles based on their average annual number of hot days, where a hot day is now defined as a day above 27 °C, and we estimate the sensitivity of income growth to the number of hot days by quintile. This evidence, which is very similar to the one presented above, is summarized in Table 3.

The indirect inference approach amounts to minimizing the distance between the data and model moments. For a given parameter vector $x = (\overline{b_1}, \theta)$, we solve and simulate the model and run on the

[14] More specifically, θ measure the efficiency with which the adaptation cost k translates into a smaller (in absolute value) sensitivity.

	Q1	Q2	Q3	Q3	Q5	J-stat	p-val
Data	-0.130	-0.099	-0.066	-0.040	–0.007	–	–
S.E.	0.075	0.053	0.022	0.010	0.009	–	–
Model	-0.118	-0.116	–0.063	-0.027	-0.012	2.068	0.559

Table 3: Model fit. This table reports the data moments and the model moments, for the estimated parameters, together with the J-statistic.

"data" consisting of these simulations the same regression that we run in the true data:

$$\Delta \log Y_{i,t} = \alpha_i + \delta_t + \sum_{q=1}^{5} \gamma_q Hot\_Days_{i,t} \times D_{i,q} + \varepsilon_{i,t}, \tag{9}$$

where $D_{i,q}$ is a dummy equal to 1 if county i belongs to quintile q according to the average number of hot days. We hence obtain a vector of model moments $\gamma(x) = (\gamma_1, \gamma_2, \gamma_3, \gamma_4, \gamma_5)$. We calculate the criterion

$$(\gamma(x) - \widetilde{\gamma})' W (\gamma(x) - \widetilde{\gamma})$$

where $\widetilde{\gamma}$ is the vector of parameters estimated in the true data, and W is a weighting matrix. In our baseline estimates, we set W equal to the identity matrix, but in section 5 we show how the results are affected for other choices of W. We then choose the vector x in order to minimize the criterion.[15] Because we have 5 target moments and only 2 parameters, the model is overidentified and it can be rejected using the standard J statistic.

The results of this procedure are presented in table 3. The model matches the five moments fairly well. This is reflected in the J-statistic of about 2, which means the model is not rejected at any conventional level of statistical significance (pval=55.9%). The values of $\overline{b_1}$ and θ that generate this behavior are listed in Table 2. The estimated $\overline{b_1}$ is large, which is necessary to fit the fact that high temperature has a large effect in cold regions with presumably little adaptation. In contrast, the estimated θ is not extremely large; reducing the sensitivity by 50% costs 0.5% of income (since $\log(0.5)/\theta$ is approximately -0.005).

[15] This minimization is performed numerically using a variety of starting points.

4 Climate change and adaptation

We use the model to predict the effect of potential climate change. We feed the model a predicted temperature increase associated with a global warming scenario, and calculate the implied change in economic output and of adaptation effort. We focus on two questions. First, how large are the income losses from potential climate change? Second, which regions in the US are most affected?

4.1 Methodology

Our calculations require two inputs: a climate forecast by county over the next century; and a model that maps temperature into income. Regarding the climate forecast, we base our results on Rasmussen et al. (2016). It turns out that there is relatively little heterogeneity across (continental) US counties in the temperature increase predicted by these climate models. Hence, as a starting point, we assume that warming is uniform across all counties. We also abstract from changes in the shape of the temperature distribution within a county – we assume that the distribution simply shifts to the right.[16] We consider the four scenarios outline in Rasmussen et al. (2016), corresponding to increases of temperature of 1.6, 2.7, 3.4, or 5.1 °C respectively.

Regarding the model, we find it useful to contrast three specifications, which are all nested in our structural model. We refer to these as the no adaptation, fixed adaptation, and endogenous adaptation models. The *no* adaptation model assumes that, both today and in the future, there is no adaptation margin. This corresponds to setting $\theta = \infty$ a priori in our structural model. The remaining parameter $\overline{b_1}$ is estimated to match the five quintiles regression coefficients as well as possible.[17] All US counties thus have the same sensitivity to weather, similar to the calculations Hsiang et al. (2017) perform for a large class of models.

The second version is the *fixed* adaptation model, which assumes the level of adaptation is fixed and cannot be changed after warming. Specifically, we assume that the structural model is correct and each county has chosen its adaptation optimally given its climate. However, for unmodeled reasons it is not possible to change the adaptation level in the future, so adaptation remains at its currently inferred level. This is essentialy equivalent to a reduced form calculation that takes into account heterogeneity across counties in terms of slopes.

The third version is the *endogenous* adaptation model, which is is our full structural model. Counties can choose to adjust their level of adaptation in response to climate change.

[16] 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.

[17] Of course, the model will not be able to fit the five quintiles regression coefficients well, since all counties have by construction the same sensitivity to temperature.

4.2 Results

Table 4 presents each model's estimates of the effect of climate change on consumption (output less adaptation costs) and total output across United States counties. We draw four main conclusions from this table and the associated figures, Figure 6 (a histogram of the losses by county) and figures 7, 8 and 21 (maps of losses by county). We discuss these conclusions from more to less obvious.

(C1) Adaptation following climate change results in lower median losses

This conclusion is of course qualitatively preordained; counties can do no worse than keeping their current adaptation level, so by optimizing it they reduce their losses. But the magnitudes of the reductions in losses is impressive. For instance, consider the 5.1 °C scenario. The median loss if adaptation remains at current levels is -4.18%, whereas it is only -1.71% if counties are allowed to adjust optimally.

(C2) Adaptation following climate change results in lower dispersion of losses

Perhaps as important from a welfare point of view, the dispersion in losses is also vastly reduced once adaptation is taken into account. Focusing again on the 5.1 °C scenario, we see that the standard deviation of losses is 2.22% with fixed adaptation and only 0.51% with endogenous adaptation. The economic mechanism is that counties that have the most to lose from climate change will be those that benefit the most from adaptation; as a result, the left tails of outcomes is strongly truncated. For instance, the 10th percentile of losses is -7.35% under the fixed adaptation scenario and only -2.31% under the endogenous adaptation scenario. This dramatic reduction in dispersion is most clear in Figure 6.

(C3) Taking into account the heterogeneity in current adaptation levels reduces the median losses and the dispersion

The median loss under the fixed adaptation case is larger than the loss under the no adaptation case. For instance in the 5.1 °C scenario, the loss is 4.18% versus 5.82%. The logic here is that climate change will increase the number of hot days, but mostly in places that are (as estimated using current data) less sensitive to hot days than the average. As a result, the losses are smaller once this heterogeneity is taken into account.[18]

(C4) Which regions lose is highly sensitive to the model considered

Figures 7, 8 and 9 depict the estimated losses under each model, again for the 5.1 °C scenario. With no adaptation, the South suffers dramatically. The logic is that Southern counties experience a large increase number of hot days, which are estimated, based on the entire US sample, to have a large negative effect on income. The fixed adaptation model, which takes into account current heterogeneity in sensitivity, projects a much less severe effect on the South. The reason is the South is currently estimated to have a low sensitivity to hot days. In an interesting reversal, the Midwest and Northeast appears to suffer relatively the most. Under endogenous adaptation, all areas experience smaller losses, but the Midwest and Northeast are still relatively the worst off. The reason is that these regions currently are highly sensitive to hot days. With endogenous adaptation, these regions can reduce their sensitivities, however they must pay the adaptation costs. These adaptation costs account for the

[18] Note that this result does not have to be true for all configurations. A sufficiently extreme global warming would increase the number of hot days everywhere and this compositional argument would have little bite then.

		median	sd	p10	p25	p75	p90
Panel A: Scenario +1.6 °C							
No adaptation model	C, Y	-1.262	1.369	-3.631	-2.495	-0.472	-0.138
Fixed adaptation	C, Y	-0.847	0.456	-1.441	-1.126	-0.569	-0.285
Endogenous adaptation	C	-0.643	0.289	-1.017	-0.856	-0.464	-0.276
	Y	0.566	0.936	-0.425	-0.208	1.489	2.009
Panel B: Scenario +2.7 °C							
No adaptation model	C, Y	-2.265	2.340	-6.259	-4.380	-0.869	-0.256
Fixed adaptation	C, Y	-1.541	0.826	-2.599	-2.035	-1.018	-0.498
Endogenous adaptation	C	-0.972	0.384	-1.421	-1.237	-0.747	-0.485
	Y	0.558	0.963	-0.494	-0.274	1.472	2.030
Panel C: Scenario +3.4 °C							
No adaptation model	C, Y	-2.873	2.936	-7.874	-5.543	-1.111	-0.328
Fixed adaptation	C, Y	-2.059	1.078	-3.389	-2.700	-1.365	-0.591
Endogenous adaptation	C	-1.220	0.455	-1.724	-1.514	-0.944	-0.586
	Y	0.480	1.020	-0.558	-0.352	1.485	2.106
Panel D: Scenario +5.1 °C							
No adaptation model	C, Y	-5.816	4.518	-12.965	-9.630	-2.918	-1.274
Fixed adaptation	C, Y	-4.176	2.220	-7.358	-5.788	-2.832	-1.945
Endogenous adaptation	C	-1.713	0.511	-2.310	-2.108	-1.350	-1.071
Endogenous adaptation	Y	0.505	1.031	-0.657	-0.430	1.472	2.053

Table 4: Estimated effect of climate change on income under different scenarios of adaptation. The statistics report the cross-sectional losses across counties. The endogenous adaptation senario's consumption is different from output, since counties can pay (lower consumption) to decrease heat sensitivty (increase output).

difference between the response of consumption and output in table 4. To summarize quantitatively these regional differences, Table 5 presents the median losses for each Census region under each model for the 5.1 °C scenario. To illustrate the difference between the different models' predictions, Table 6 reports the correlation across counties between the predicted losses for two differents models. The predictions of the model with no adaptation (i.e., constant and equal sensitivies countrywide) are actually negatively correlated (-0.12 or -0.39) with those of the models that either take into account observed adaptation today ("fixed adaptation"), or allows for further adaptation ("endogenous adaptation" model). This demonstrates quantitatively the importance of adaptation technology.

		North	Midwest	South	West
No adaptation	C,Y	-2.56	-4.57	-10.58	-1.59
Fixed adaptation	C,Y	-4.83	-4.85	-3.68	-2.79
Endogenous adaptation	C	-2.19	-1.89	-1.43	-1.71
Endogenous adaptation	Y	-0.58	0.20	1.63	-0.54
Number of counties		186	775	846	354
Population (in Millions)		56.50	68.20	77.40	123.70

Table 5: The effect of the differnt scenarios on consumption and output by Census region.

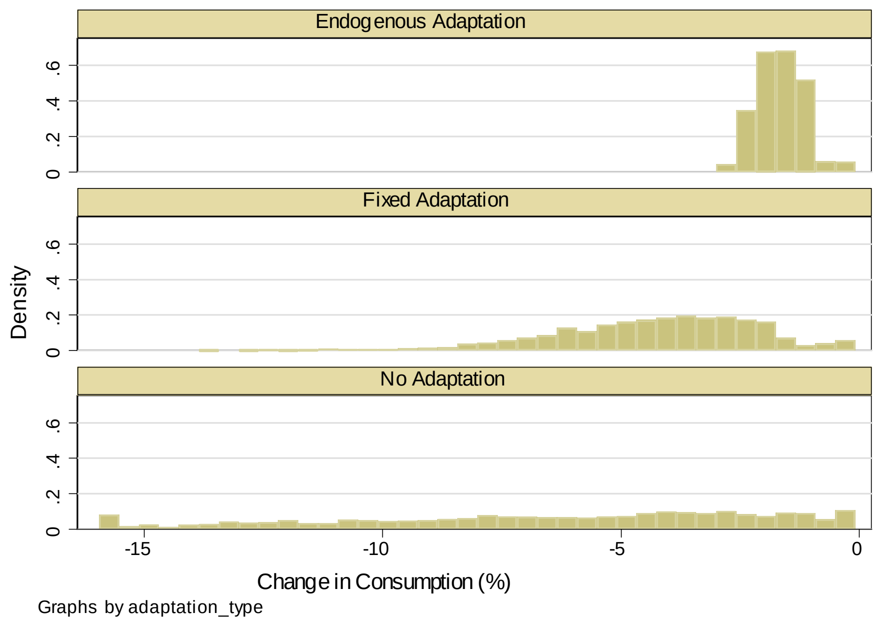

Figure 6: Histogram of model projections for county level consumption losses due to climate change in the 5.1C scenario. Losses are windsorized at the 1% level.

		No adaptation	Fixed adaptation	Endogenous adaptation	
		C,Y	C,Y	C	Y
No adaptation	C,Y	1.00			
Fixed adaptation	C,Y	-0.12	1.00		
Endogenous adaptation	C	-0.39	0.84	1.00	
	Y	-0.93	0.31	0.59	1.00

Table 6: County level correlations of the losses under the different model for the 5.1C warming scenario.

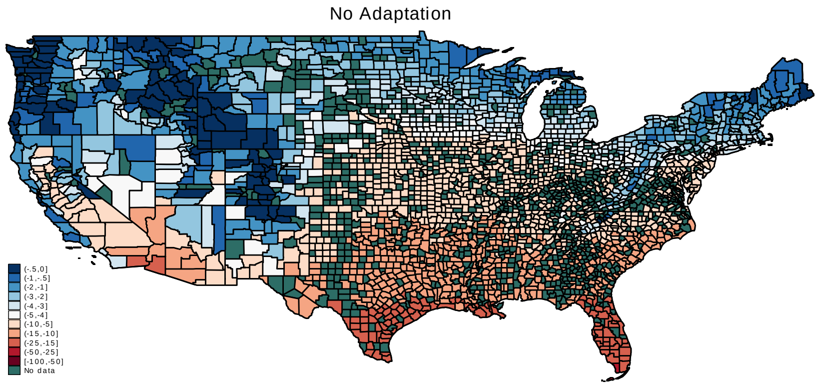

Figure 7: The map displays the percentage loss of consumption due to a 5.1C warming under the no adaptation model.

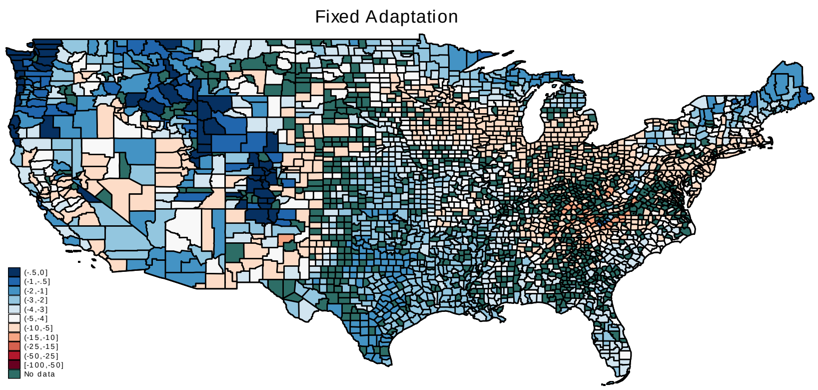

Figure 8: The map displays the percentage loss of consumption due to a 5.1C warming under the fixed adaptation model.

4.3 Caveats

There are a number of limitations of our work. Some reflect our design: we focus solely on the effect of temperature and abstract from other weather or climate variables, in particular extreme events or sea level rise. We also focus on the effect on economic production rather than on other measures of welfare.

Most importantly, we need to extrapolate from currently observed behavior to future behavior. This requires two steps: first, estimating the effect of the higher temperature on output; second, estimating the changes in adaptation. The former reflects, to some extent, mechanical extrapolation: the county that is currently the hottest in the US[19] will become even warmer after climate change. To forecast the effect this higher temperature will have on its output, we need to some extent extrapolation. Table 7 quantifies this by showing, for each scenario of climat echange, how many counties will have an average number of hot days (days above 27C) that is greater than the 95th, 99th or 100th percentile of the currently observed distribution. For instance, if the temperature increases by 3.4C, 4.9% of counties will

[19] Which is XXX according to our data.

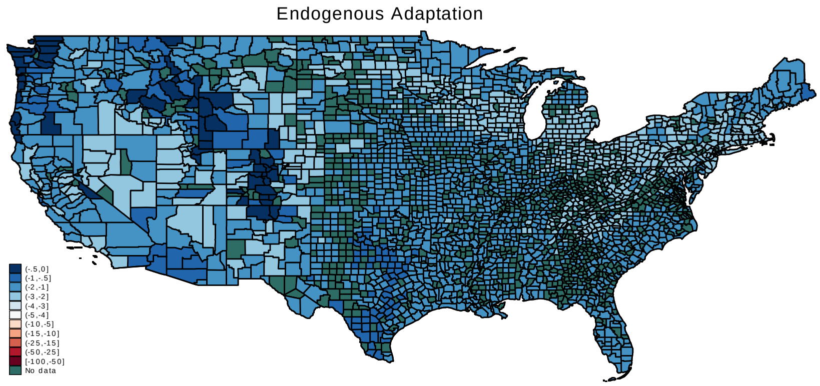

Figure 9: The map displays the percentage loss of consumption due to a 5.1C warming under the endogenous adaptation model.

Scenario	p95	p99	pmax
+1.6C	17.6%	3.9%	1.2%
+2.7C	26.7%	9.9%	3.1%
+3.4C	32.3%	15.1%	4.9%
+5.1C	48.1%	24.9%	12.2%

Table 7: Measuring extrapolation. This table reports for each climate change scenario the percentage of counties with an average number of hot days post-climate change that is greater than the corresponding percentiles of the distribution of the historical average.

have an average number of hot days greater than any county today. For these counties, we are certainly "extrapolating". Figure 10 presents the corresponding distributions.

The other key assumption required for the "endogenous adaptation" case is that the costs of adaptation remain stable. It is difficult to forecast what will happen over time regarding these costs. Plausibly, new technologies will reduce adaptation costs, in which case our results are an upper bound on the losses. But it is also possible that climate change will reduce the set of technologies that can be used - for instance by changing the precipitation patterns. There are also some general equilibrium forces that we do not model, such as the change of relative prices corresponding to the output of different regions.

5 Robustness of structural model results

In this section, we present some extensions of our baseline model. In particular, we consider alternative functional forms for two mappings: (a) the mapping of temperature to productivity, (b) the mapping of adaptation cost k to sensitivity $b_1(k)$. We also consider alternative objective functions for the estimation method. Finally, we show how the results change if intertemporal trade (i.e. borrowing and lending)

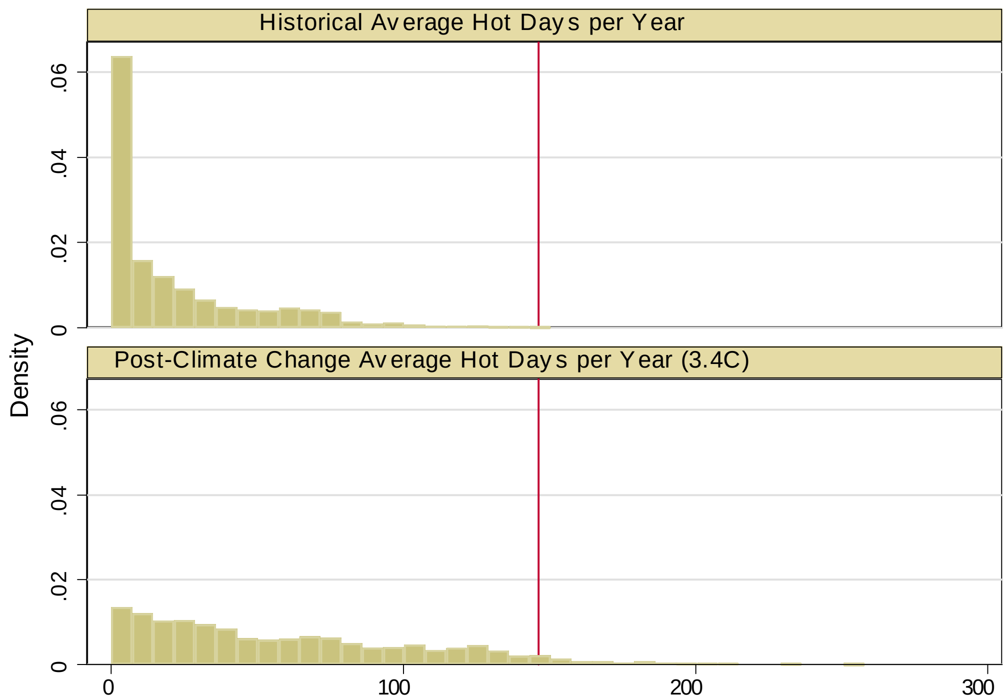

Figure 10: The figure plots the histogram of the distribution of average hot days per year across counties, for the historical data and for our forecast post-climate change in the 3.4C scenario. The red line denotes the maximum across counties of the average number of hot days today.

between counties is allowed. Intertemporal trade allows counties to insulate their consumption from their output fluctuations.

5.1 Mapping of temperature to productivity

Our baseline model, inspired by the empirical results, assumes that productivity is unaffected by temperature, up to a level $\overline{T}$, then falls linearly with temperature for $T > \overline{T}$. We set $\overline{T} = 26\,^{\circ}\mathrm{C}$. Here we consider two variants on this model. First, we simply change the value of $\overline{T}$. We then re-estimate the model and re-run all the counterfactuals with the new estimated parameters. Second, we consider the possibility of non-linear effects of temperature on productivity, that is we assume

$$\begin{aligned} \log A_{it} &= b_0 \text{ if } T_{it} < \overline{T}, \\ &= b_0 - b_1(k)(T_{it} - \overline{T})^2 \text{ if } T_{it} \geq \overline{T}, \end{aligned}$$

and we also consider different values for $\overline{T}$. The resulting estimated parameters, moment fits, and counterfactuals are summarized in Tables 8, 9 and 10 respectively.

The estimated slope $\overline{b_1}$ of temperature on productivity (absent any adaptation) is higher if $\overline{T}$ is larger, since the model is required to fit the effect of hot days measured in the data (see rows 2-3 and 9-11 of table 8). In terms of model fit, all these models have a roughly similar fit, as seen in rows 3-4 and 10-12 of table 9. None is rejected, and all have p-values in the range of 43%-56%, corresponding to J-statistics between 2 and 3. Third, these models imply different economic losses in the $+5.1\,^{\circ}\mathrm{C}$ climate change scenario, as shown in table 10. It would be useful to distinguish among these models to forecast the extant of losses. We plan to do this by adding more precise measures of data moments (e.g., the responses to different bins of temperatures rather than to hot days as a whole) in our estimation procedure. Note, however, that the general features (C1)-(C4) we noted in the previous section remain. In this sense, our key results appear unaffected by the exact functional form used.

5.2 Functional form of adaptation technology

The baseline model assumes a simple functional form $h(k) = e^{-\theta k}$. But of course, we have little knowledge of the technology for adaptation, and it is not guaranteed that this functional form is the best approximation of the data. This leads us to consider some alternatives, for instance $h(k) = \max(1-\theta k, 0)$ (linear case, row 6 in Table 8), $h(k) = \max\left(1 - \theta k^2, 0\right)$ (quadratic case, row 7) or $h(k) = \max(1-\theta\sqrt{k}, 0)$ (square root case, row 8). The linear case is statistically rejected ($p = 0.4\%$) as it implies that the fourth and fifth quintiles have sensitivities much lower than in reality. The quadratic case and the square root case also underestimate the sensitivity of the fifth quintile, but they fit reasonably well the other moments. Note that the quadratic case implies "increasing returns" to adaptation. As a result, the model moments are constant over the first three quintiles before falling off quickly. In contrast, the square root

	$\overline{b_1}$	θ
Baseline	0.21	131.21
	(0.02)	(0.18)
T = 28 °C	1.09	131.83
	(0.61)	(5.79)
T = 24 °C	0.13	69.42
	(0.01)	(313.87)
Moments weighted by SE	0.18	106.85
	(0.00)	(0.07)
Moments weighted by pct dev	0.22	167.26
	(0.01)	(0.33)
h(k) linear	0.20	53.20
	(0.01)	(0.09)
h(k) quadratic	0.16	916.14
	(0.00)	(0.03)
h(k) square-root	0.20	5.97
	(0.01)	(0.30)
Quadratic effect of T on productivity	0.08	137.96
	(0.00)	(980.89)
Quadratic + T = 24 °C	0.03	108.16
	(0.00)	(0.03)
Quadratic + T = 28 °C	2.30	63.00
	(2.00)	(55.93)

Table 8: Robustness: estimated parameter values and standard errors for each of the models considered in section 5.

	Q1	Q2	Q3	Q4	Q5	J stat	pval
Data	-0.130	-0.099	-0.066	-0.040	-0.007		
Baseline	-0.118	-0.116	-0.063	-0.027	-0.012	2.068	0.559
$\overline{T} = 28\,°\mathrm{C}$	-0.123	-0.115	-0.057	-0.026	-0.011	2.544	0.467
$\overline{T} = 24\,°\mathrm{C}$	-0.127	-0.107	-0.059	-0.031	-0.016	2.068	0.558
Moments weighted by SE	-0.104	-0.107	-0.073	-0.033	-0.014	1.442	0.696
Moments weighted by pct dev	-0.124	-0.112	-0.049	-0.021	-0.009	4.050	0.256
$h(k)$ linear	-0.114	-0.116	-0.066	-0.004	-0.000	13.401	0.004
$h(k)$ quadratic	-0.096	-0.098	-0.101	-0.041	-0.002	3.145	0.370
$h(k)$ square-root	-0.111	-0.105	-0.087	-0.031	-0.002	2.244	0.523
Quadratic effect of T on productivity	-0.122	-0.115	-0.058	-0.025	-0.011	2.630	0.452
Quadratic + $\overline{T} = 24\,°\mathrm{C}$	-0.125	-0.112	-0.057	-0.028	-0.013	2.137	0.544
Quadratic + $\overline{T} = 28\,°\mathrm{C}$	-0.129	-0.103	-0.057	-0.035	-0.020	2.730	0.435

Table 9: Robustness: fit of the various models considered in section 5. The table reports the data and model implied moments (regression coefficient of income growth on hot days) for each of the five quintiles, together with the J-statistic of model overidentification and the associated p-value.

	No Adaptation		Fixed Adaptation		Endogenous adaptation	
	Median	SD	Median	SD	Median	SD
Baseline	-5.816	4.518	-4.176	2.220	-1.713	0.511
$\overline{T} = 28\,°\mathrm{C}$	-7.707	8.232	-5.552	3.002	-2.179	0.636
$\overline{T} = 24\,°\mathrm{C}$	-5.441	3.376	-4.175	1.645	-2.310	0.616
Moments weighted by SE	-2.291	1.878	-4.609	2.275	-2.037	0.589
Moments weighted by pct dev	-0.811	0.676	-3.578	2.110	-1.360	0.426
$h(k)$ linear	-5.872	4.558	-0.926	3.684	-0.614	0.777
$h(k)$ quadratic	-5.858	4.548	-3.695	4.287	-1.866	1.264
$h(k)$ square root	-5.837	4.533	-4.580	3.260	-1.380	1.019
Quadratic effect of T on productivity	-7.431	7.565	-5.914	2.536	-2.011	0.505
Quadratic + $\overline{T} = 24\,°\mathrm{C}$	-6.373	5.646	-5.007	1.919	-2.042	0.484
Quadratic + $\overline{T} = 28\,°\mathrm{C}$	-11.450	11.130	-9.982	8.077	-6.678	1.719

Table 10: Robustness. The table reports the estimated effect of a uniform 5.1C warming for each of the models considered in Section 5, under the three cases (no adaptation model, fixed adaptation, and endogenous adaptation). The statistics report the median and standard deviation across counties of the losses.

case implies (like our baseline model) "decreasing returns" and the pattern of reduction of the coefficient is more regular (as is the data).

In terms of model implications for the cost of climate change, the range of estimated losses is similar (except for the linear model which is strongly rejected as we showed). For instance, the median loss under fixed (endogenous) adaptation is -4.17% (-1.71%) for the baseline model, as opposed to -3.69% (-1.87%) for the quadratic model and -4.58% (-1.38%) for the square root model. Perhaps more important, the other conclusions C1-C4 drawn above hold for the different functional forms. This suggests a certain robustness of our findings to the exact way adaptation is modeled.

5.3 Estimation targets

Our baseline estimates are based on a simple criterion – we weight all five moments equally. From a statistical perspective, it is recommended (Hansen (1982)) to use as weighting matrix the inverse of the covariance matrix of moments. From an economic perspective, one might want to define model errors (i.e., deviation between data and model moments) be measured in percentage terms. Rows 4 and 5 implement these objective functions. Both of them lead to put significantly more weight on the quintiles 4 and 5 which are measured more precisely and have smaller absolute values. The results for the fixed adaptation and endogenous adaptation models are little changed. However, the model with no adaptation behaves very differently. To fit the fourth and fifth quintiles, the estimator picks a much lower sensitivity $\overline{b_1}$. As a result, the median and standard deviation of estimated losses are lower than in our baseline estimation method.

5.4 Trade

The model assumes that counties are autarkic, i.e. consumption equals output, $C_{it} = Y_{it}$. Instead we assume now that counties can borrow and lend goods to each other. The resource constraint is now at the nation level:

$$\sum_{i=1}^{N} C_{it} = \sum_{i=1}^{N} Y_{it},$$

where we abstract from foreign trade. We assume complete markets, which is the most extreme form of borrowing and lending imaginable. In that case, the equilibrium is characterized by: two conditions. First, the marginal rate of substitution of leisure and consumption must be equalized in each county to the marginal product of labor, leading to:

$$N_{it}^{\psi} C_{it}^{\gamma} = \alpha A_{it} N_{it}^{\alpha-1}$$

Second, the optimal risk-sharing condition states that

$$C_{it}^{-\gamma} \alpha_i = \lambda_t,$$

where α_i is the Pareto weight of county i and λ_t is a multiplier. In the case with no aggregate uncertainty (e.g. weather shocks average out over the nation), then λ_t is constant. This implies that C_{it} is constant as well. Overall, we obtain

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

and

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

and

$$C_{it} = \overline{C_i}.$$

Results to be added.

6 Conclusion

To be added.

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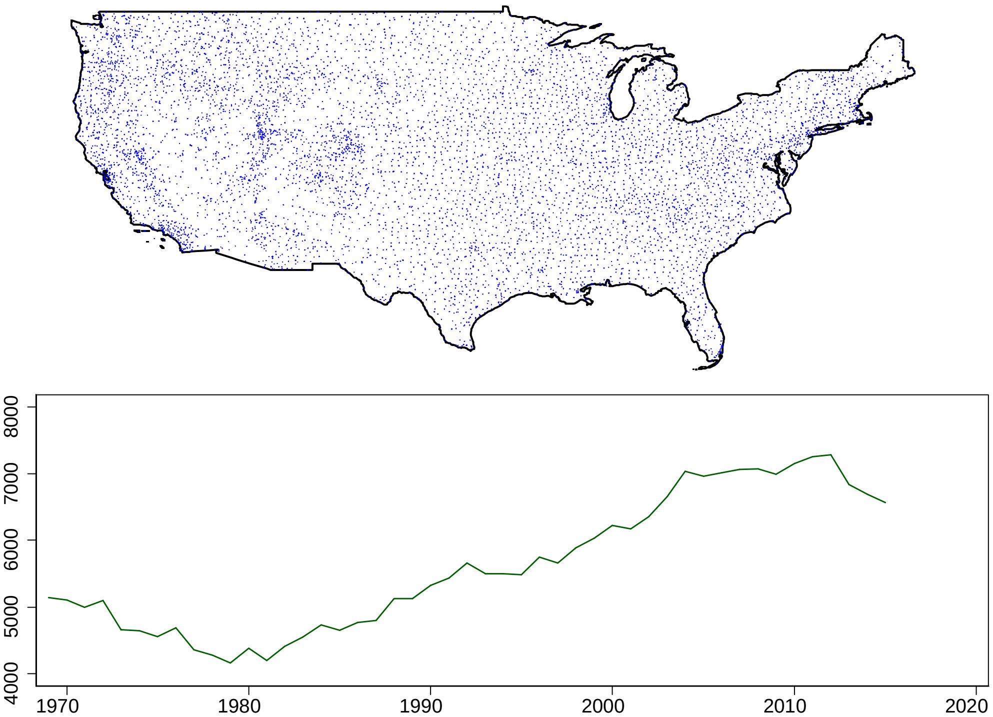

Figure 11: (Top): The figure plots the locations of weather stations that are used in 2000 in our calculations of county-specific weather. (Bottom): This figure plots the number of weather stations that are used each year in our calculations of county-specific weather.

8 Appendix

8.1 Summary Statistics Table

8.2 Station statistics

Figure 11 depicts the number of stations used in our dataset to construct our measures of weather and the locations of the stations used for the year 2000 (as an example).

8.3 Current Climate

Figure 12 depicts the average annual temperature and the average annual number of "hot days" for each US county.

8.4 Robustness of Empirical results

In this subsection, we present some additional empirical results that relate to the baseline results. These results are overall consistent with those reported in Deryugina and Hsiang (2014). Table 12 presents the results. The first column simply reports the results when counties are weighted by their population.

	mean	sd	min	p5	p50	p95	max	count
(days in range)								
-15 °C or less	4.87	10.50	0.00	0.00	0.00	26.00	178.00	92738
-15 °C,-12 °C	3.48	4.95	0.00	0.00	1.00	14.00	45.00	92738
-12 °C,-9 °C	5.67	6.62	0.00	0.00	3.00	19.00	55.00	92738
-9 °C,-6 °C	8.77	8.53	0.00	0.00	7.00	24.00	73.00	92738
-6 °C,-3 °C	13.26	10.66	0.00	0.00	13.00	31.00	74.00	92738
-3 °C,0 °C	19.42	12.81	0.00	0.00	20.00	40.00	88.00	92738
0 °C,3 °C	24.63	13.47	0.00	2.00	25.00	47.00	117.00	92738
3 °C,6 °C	29.26	12.51	0.00	8.00	29.00	49.00	132.00	92738
6 °C,9 °C	30.86	11.20	0.00	16.00	30.00	49.00	134.00	92738
9 °C,12 °C	32.16	10.45	0.00	19.00	31.00	49.00	154.00	92738
12 °C,15 °C	30.29	12.69	0.00	0.00	31.00	47.00	216.00	92738
15 °C,18 °C	33.87	10.06	0.00	20.00	33.00	49.00	157.00	92738
18 °C,21 °C	37.60	12.31	0.00	20.00	38.00	55.00	306.00	92738
21 °C,24 °C	36.30	16.46	0.00	4.00	37.00	60.00	276.00	92738
24 °C,27 °C	31.13	24.15	0.00	0.00	29.00	73.00	223.00	92738
27 °C,30 °C	17.43	23.44	0.00	0.00	6.00	68.00	169.00	92738
30 °C or more	3.11	9.38	0.00	0.00	0.00	18.00	130.00	92738
(in log differences)								
Personal Income Per Capita	5.54	6.80	-107.49	-3.30	5.11	15.27	130.48	90568
Wages and Salaries	5.74	6.41	-105.11	-2.96	5.41	15.25	124.44	90568
Propietor Income	4.94	32.18	-637.47	-38.67	5.33	46.93	657.68	90068
Farm Propietor Income	1.84	93.11	-949.66	-141.22	2.86	140.05	870.62	68110
Nonfarm Propietor Income	5.35	14.02	-288.79	-13.98	5.65	23.29	413.44	90527
(in thousands)								
Population	108.44	334.50	0.20	3.15	28.05	477.47	10170.29	92738

Table 11: Summary statistics of primary variables of analysis. Units are in parentheses at the top of each section.

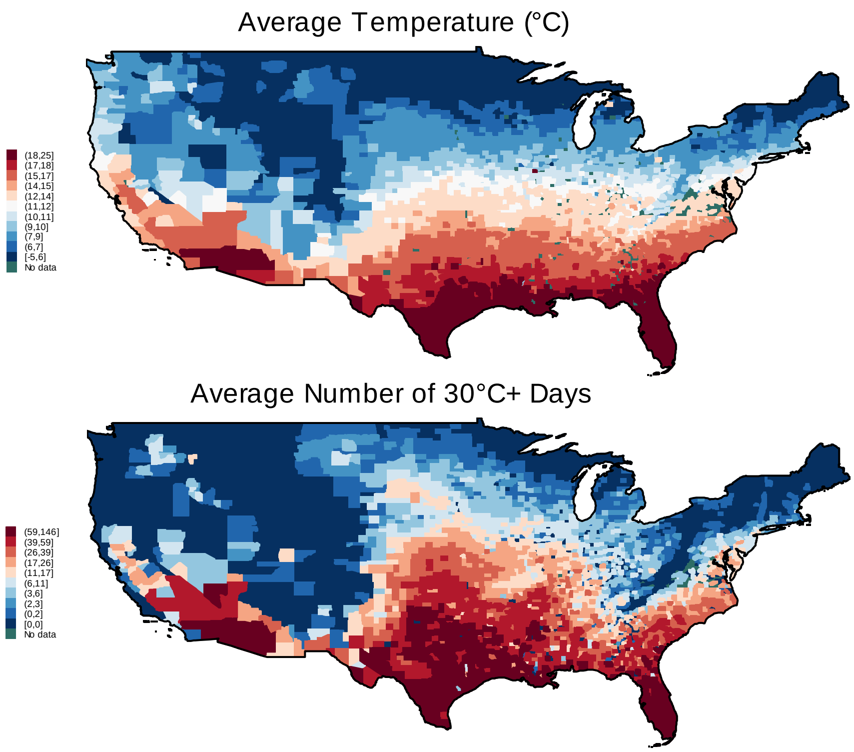

Figure 12: The top panel depicts the average temperature of each county; the bottom panel depicts the average number of days per year with an average temperature above 30°C. Weather statistics calculated over the period 1969-2015.

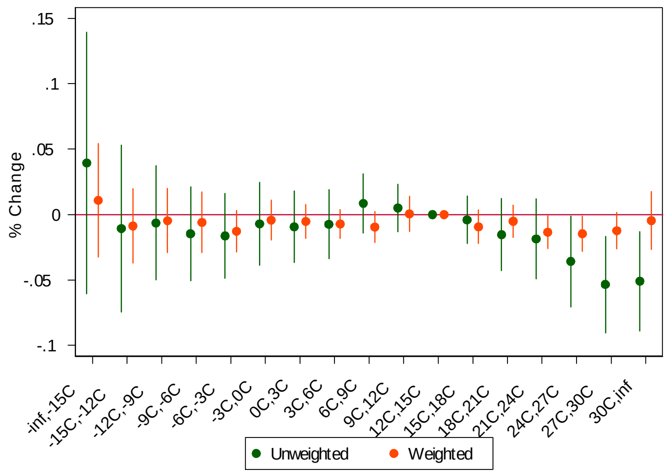

Figure 13: The circles denote unweighted (green) and population weighted (orange) estimates of β_k in equation (1), and the bars reflect the associated +/- 2 standard error bands.

Figure **??** depicts the resulting coefficients together with those of the baseline model 1. The resulting coefficients on hot days are smaller (and less precisely estimated), suggesting that small counties are important drivers of the results. The second column reports the results when the time effect is omitted from the regression. The third column uses the change in the number of days in a given bin (rather than the level) as the variable of interest. This specification may be preferable if there are trends in the data. The results are fairly similar, though less statistically significant. The fourth and fifth columns illustrate the dynamic effects of the weather shock. The specification is:

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

and the results are also presented in graphical form in Figure 14. As can be seen the coefficients on the hot days lagged are now significantly positive. The hypothesis $\beta_k + \beta_k^{lag} = 0$ (i.e., there is no long-run effect on income) can be rejected. Finally, the last column shows the effect of adding precipitation as a control variable. The specification is

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

where the $Bin_{k,i,t}^P$ are bins of precipitation for county i in year t, defined analogously to those for temperature. The results for temperature remain similar once precipitation is controlled for.

We next consider which income categories account for the result. To do so, we simply replace total income growth with some subcomponents Z and estimate the same specification:

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

The results for Z corresponding to (a) wages and salaries, (b) proprietor income, (c) nonfarm proprietor income, and (d) farm proprietor income, are depicted in Figure 15 and the coefficient estimates are in 13. The estimated effects are much larger for proprietor income, and these appear to be driven by

	Population Weighted	No Time FE	Bins First Difference	Lagged Current Coefs	Lagged Lagged Coefs	With PRCP Controls
-15 °C 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)
-15 °C,-12	-0.00866	0.0273	-0.000443	-0.0112	0.00115	-0.00953
	(-0.82)	(0.51)	(-0.01)	(-0.39)	(0.03)	(-0.34)
-12 °C,-9 °C	-0.00464	0.0268	0.00570	0.00232	-0.00492	-0.00500
	(-0.35)	(0.66)	(0.18)	(0.08)	(-0.22)	(-0.16)
-9 °C,-6 °C	-0.00591	-0.0171	0.00586	-0.00909	-0.00655	-0.0133
	(-0.56)	(-0.52)	(0.27)	(-0.48)	(-0.32)	(-0.75)
-6 °C,-3 °C	-0.0127	-0.0165	0.00562	-0.00963	-0.00202	-0.0153
	(-2.00)	(-0.58)	(0.27)	(-0.59)	(-0.11)	(-1.03)
-3 °C,0 °C	-0.00417	0.00936	-0.00167	-0.00369	0.00577	-0.00655
	(-0.65)	(0.32)	(-0.10)	(-0.22)	(0.36)	(-0.39)
0 °C,3 °C	-0.00519	-0.00700	0.00890	-0.00843	-0.00357	-0.00871
	(-0.97)	(-0.25)	(0.46)	(-0.52)	(-0.26)	(-0.55)
3 °C,6 °C	-0.00713	-0.0123	0.0139	-0.00515	-0.0104	-0.00705
	(-1.38)	(-0.54)	(0.99)	(-0.42)	(-0.96)	(-0.54)
6 °C,9 °C	-0.00949	0.00482	0.0112	0.00832	-0.0104	0.00886
	(-1.34)	(0.25)	(0.75)	(0.77)	(-0.89)	(0.76)
9 °C,12 °C	0.000599	0.0112	-0.00272	0.00207	0.00359	0.00524
	(0.13)	(0.90)	(-0.20)	(0.23)	(0.36)	(0.62)
15 °C,18 °C	-0.00931	-0.00242	0.000935	-0.00719	-0.00353	-0.00384
	(-1.64)	(-0.20)	(0.05)	(-0.97)	(-0.31)	(-0.48)
18 °C,21 °C	-0.00505	-0.0109	-0.0185	-0.0210	0.0153	-0.0156
	(-0.99)	(-0.56)	(-1.04)	(-1.36)	(1.06)	(-1.05)
21 °C,24 °C	-0.0135**	-0.00437	-0.0174	-0.0242	0.0164	-0.0190
	(-2.76)	(-0.22)	(-1.04)	(-1.55)	(1.15)	(-1.25)
24 °C,27 °C	-0.0146*	-0.0157	-0.0351	-0.0419*	0.0329*	-0.0363
	(-2.25)	(-0.52)	(-1.78)	(-2.10)	(2.08)	(-1.90)
27 °C,30 °C	-0.0123	-0.0625*	-0.0266	-0.0609**	0.0241	-0.0543**
	(-1.57)	(-2.16)	(-1.31)	(-2.81)	(1.46)	(-2.73)
30 °C 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 12: Estimates of the baseline specification (Equation 1) 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.

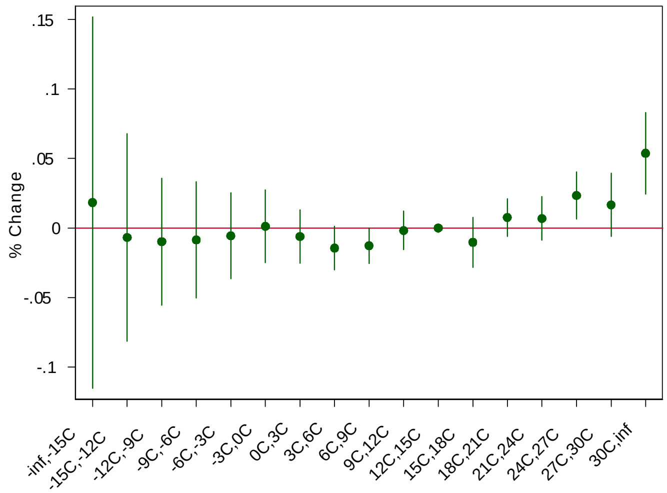

Figure 14: The green circles denote estimates of β_k^{lag} in equation (12), and the bars reflect the associated +/- 2 standard error bands.

farm proprietor income. Figure 16 shows the results if one estimates equation 11 for farm proprietor income by quintile of temperature. The same pattern emerges of a sensitivity that is larger for the colder counties (with one exception for the first quintile in the 27C-30C range).

We next turn to the decomposition between weekends and weekdays, a useful placebo test proposed by Deryugina and Hsiang (2014). We estimate the specification is:

$$\Delta \log Y_{i,t} = \alpha_i + \delta_t + \sum_{k=1}^{K} \beta_k^{WD} Bin_{k,i,t}^{WD} + \sum_{k=1}^{K} \beta_k^{WE} Bin_{k,i,t}^{WE} + \varepsilon_{i,t}, \tag{12}$$

where

$$\begin{aligned} Bin_{k,i,t}^{WD} &= \text{\# of weekdays in bin } k \text{ in county } i \text{ year } t, \\ Bin_{k,i,t}^{WE} &= \text{\# of weekend days in bin } k \text{ in county } i \text{ year } t. \end{aligned}$$

The results are shown in Figure **??** and in the first column of Table 14. We also find that the results are overall driven by weekdays. However, weekend effects are imprecisely estimated. Moreover, the weak weekend effect results from the combination of a positive effect on wages and salaries and a negative effect on farm proprietor income.

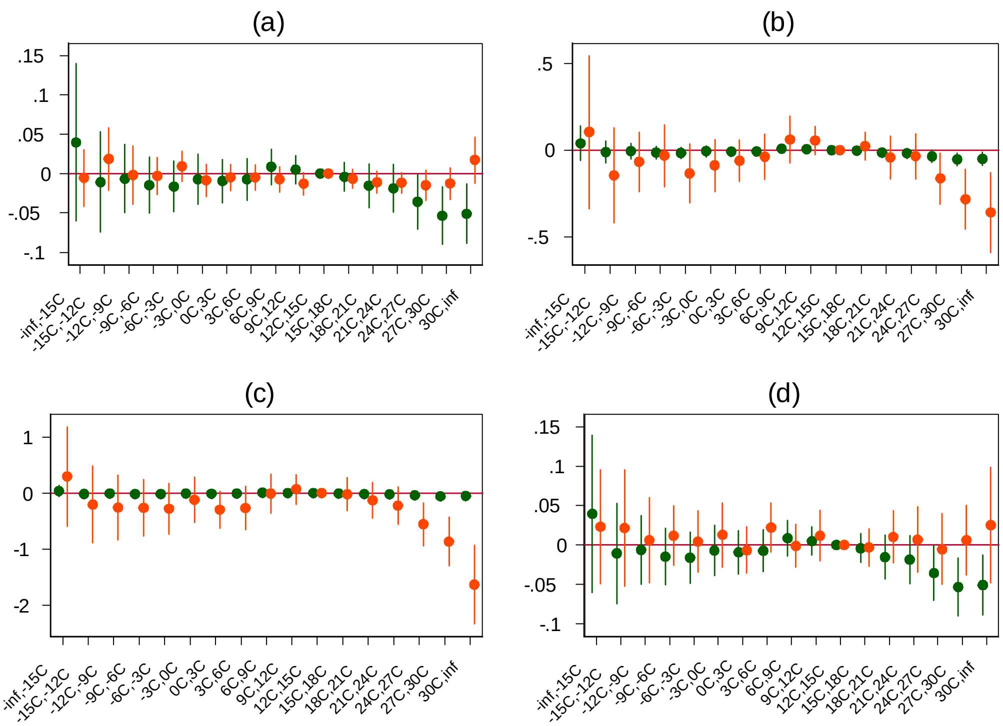

Figure 15: The circles denote estimates of β_k in equation (1), and the bars reflect the associated +/-2 standard error bands. Green circles are effect on Personal Income per Capita and oragne circles are (a) Wages and Salaries (b) Proprietors Income (c) Nonfarm Proprietors Income (d) Farm Propreitors Income. (All in log differences)

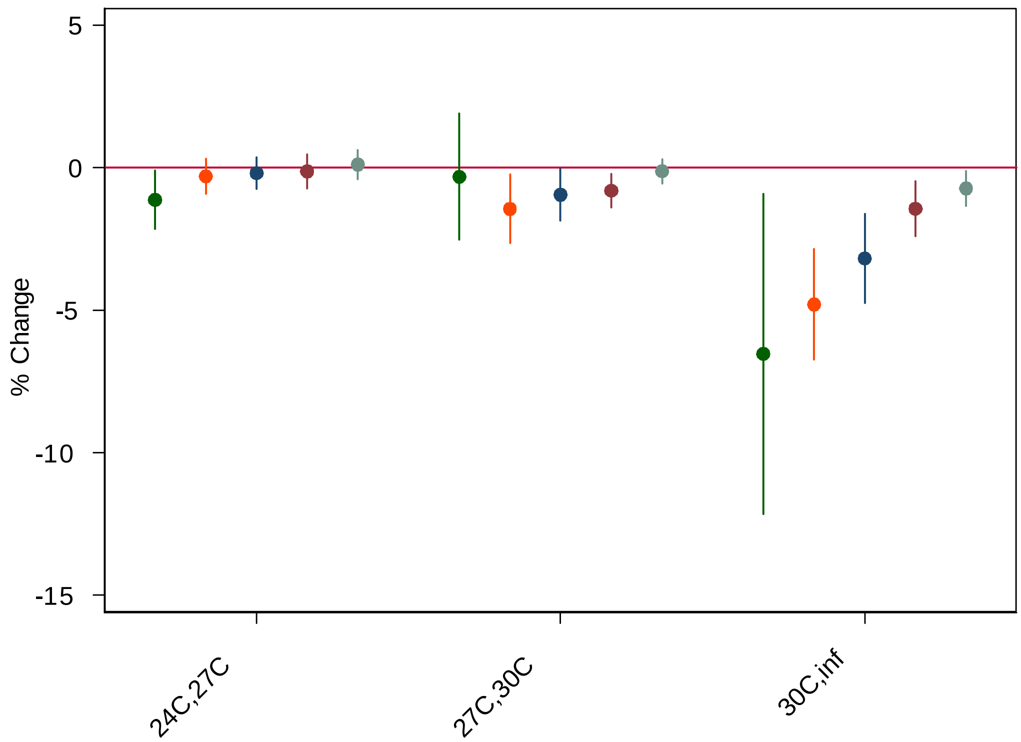

Figure 16: The circles denote estimates of β_k in equation (1) for $k = 15, 16, 17$ (three hottest temperature bins), for each of the five groups of counties (quintiles ordered by average temperature), where the response variable is Farm Proprietor Income. The bars reflect the associated +/- 2 standard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

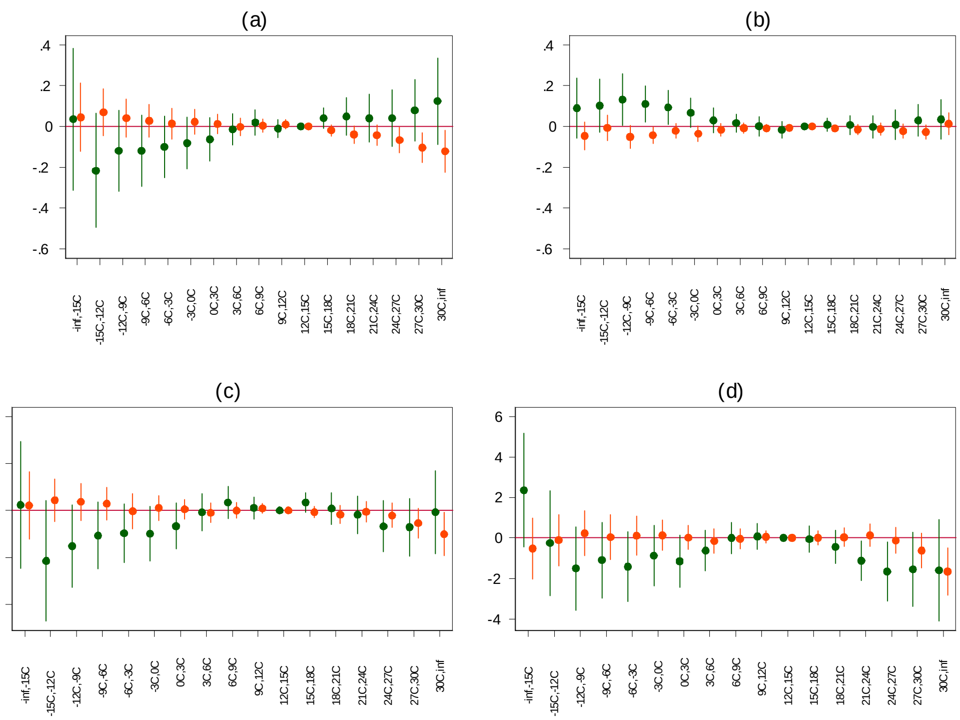

Figure 17: The circles denote estimates of β_k in equation (1), and the bars reflect the associated +/- 2 standard error bands. Green circles are effects on Weekdays and orange circles are effects on weekends. Values are (a) Personal Income Per Capita (b) Wages and Salaries (c) Proprietors Income (d) Farm Proprietors Income. (All in log differences)

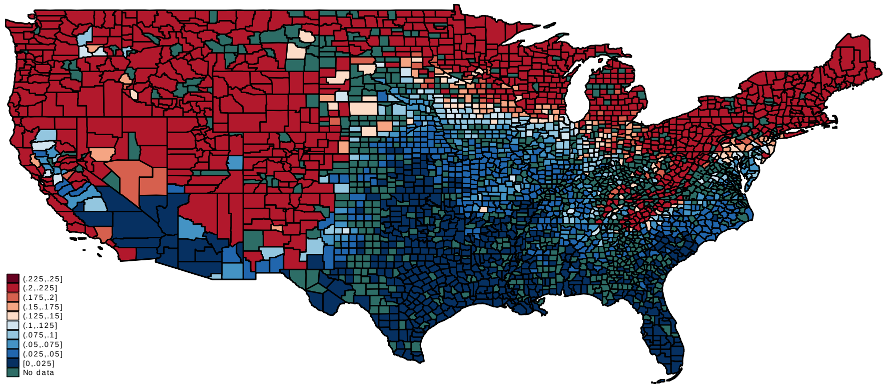

Figure 18: Sensitivity Given Current Environment

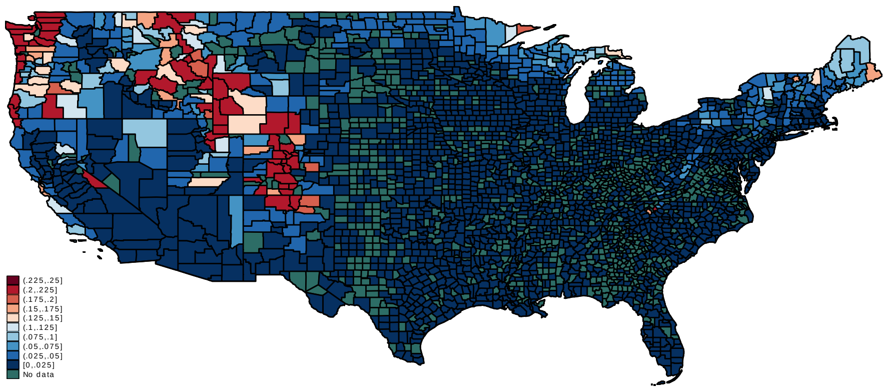

Figure 19: Model Projections of Sensitivies Given Adaptation to Climate Change in the 5.1C warming scenario.

8.5 Estimated Sensitivity to Temperature from structural model

Figure 18 depicts the estimated sensitivity to hot days in the current environment. Figure 19 shows how the model projects these sensitivities will change given climate change, after adaptation has taken place.

8.6 Adaptation choices in the structural model

In order to understand the logic of the endogenous adaptation model, it is helpful to see its implications for adaptation costs and sensitivity to weather. Figure 20 presents each county's 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 costs. Figure 21 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.

	Income	Wage	Transf.	Div.Int.	Nonfarm	Farm
-15 °C 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)
-15 °C,-12 °C	-0.00312	0.0186	-0.0108	0.0151	-0.0489	-1.186*
	(-0.09)	(0.94)	(-0.50)	(0.64)	(-0.67)	(-2.37)
-12 °C,-9 °C	-0.0102	-0.00191	-0.0114	-0.00282	0.0416	-0.901*
	(-0.46)	(-0.10)	(-0.66)	(-0.13)	(0.94)	(-2.28)
-9 °C,-6 °C	-0.0170	-0.00293	-0.0182	-0.0140	0.0244	-0.695*
	(-0.95)	(-0.25)	(-1.33)	(-0.84)	(0.56)	(-2.18)
-6 °C,-3 °C	-0.0197	0.00917	-0.00404	-0.0175	-0.00397	-0.766*
	(-1.22)	(0.97)	(-0.32)	(-1.26)	(-0.12)	(-2.30)
-3 °C,0 °C	-0.0105	-0.00837	-0.00414	-0.00176	0.0152	-0.882**
	(-0.64)	(-0.82)	(-0.40)	(-0.14)	(0.37)	(-3.00)
0 °C,3 °C	-0.0114	-0.00474	-0.00169	-0.0184	-0.0168	-0.823*
	(-0.82)	(-0.57)	(-0.20)	(-1.65)	(-0.71)	(-2.24)
3 °C,6 °C	-0.00912	-0.00472	-0.00233	-0.0170	-0.00629	-0.360
	(-0.70)	(-0.59)	(-0.28)	(-1.52)	(-0.21)	(-1.01)
6 °C,9 °C	0.00651	-0.00739	0.00313	-0.0137	-0.00659	-0.0558
	(0.59)	(-0.93)	(0.52)	(-1.24)	(-0.19)	(-0.15)
9 °C,12 °C	0.00192	-0.0126	0.00515	-0.0101	0.0152	-0.210
	(0.21)	(-1.81)	(1.03)	(-1.09)	(0.49)	(-0.69)
15 °C,18 °C	-0.00687	-0.00647	-0.000331	-0.0164	-0.00833	-0.227
	(-0.73)	(-1.09)	(-0.07)	(-1.85)	(-0.26)	(-0.68)
18 °C,21 °C	-0.0169	-0.0108	-0.00155	-0.0192	-0.0432	-0.681
	(-1.16)	(-1.54)	(-0.26)	(-1.67)	(-1.15)	(-1.74)
21 °C,24 °C	-0.0214	-0.0117	0.00245	-0.0254	-0.00338	-0.898*
	(-1.30)	(-1.81)	(0.36)	(-1.85)	(-0.10)	(-2.53)
24 °C,27 °C	-0.0366	-0.0149	0.00239	-0.0268	-0.000767	-1.131*
	(-2.00)	(-1.56)	(0.34)	(-1.69)	(-0.02)	(-2.21)
27 °C,30 °C	-0.0562**	-0.0124	-0.00793	-0.0199	-0.0898	-0.322
	(-3.03)	(-1.25)	(-1.17)	(-1.31)	(-0.95)	(-0.29)
30 °C 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 13: 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.

	Personal Income Per Capita		Wages and Salaries		Nonfarm Wages and Salaries	
	Weekdays	Weekend	Weekdays	Weekend	Weekdays	Weekend
-15 °C 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)
-15 °C,-12 °C	-0.209	0.0722	0.101	-0.0107	-0.276	-0.103
	(-1.73)	(1.49)	(1.38)	(-0.36)	(-0.20)	(-0.18)
-12 °C,-9 °C	-0.121	0.0397	0.125	-0.0486	-1.488	0.196
	(-1.35)	(0.81)	(1.91)	(-1.80)	(-1.47)	(0.39)
-9 °C,-6 °C	-0.119	0.0268	0.103*	-0.0436*	-1.097	0.0435
	(-1.47)	(0.74)	(2.07)	(-2.30)	(-1.15)	(0.08)
-6 °C,-3 °C	-0.0971	0.0161	0.0926*	-0.0217	-1.426	0.104
	(-1.40)	(0.44)	(2.36)	(-1.05)	(-1.62)	(0.22)
-3 °C,0 °C	-0.0802	0.0232	0.0651	-0.0343	-0.871	0.122
	(-1.40)	(0.77)	(1.81)	(-1.84)	(-1.13)	(0.34)
0 °C,3 °C	-0.0605	0.0130	0.0295	-0.0162	-1.164	0.00732
	(-1.22)	(0.54)	(0.96)	(-1.04)	(-1.73)	(0.03)
3 °C,6 °C	-0.0162	-0.00173	0.0127	-0.0104	-0.634	-0.157
	(-0.47)	(-0.08)	(0.59)	(-0.79)	(-1.29)	(-0.54)
6 °C,9 °C	0.0197	0.00470	0.00208	-0.00948	-0.00687	-0.0530
	(0.68)	(0.29)	(0.10)	(-1.16)	(-0.02)	(-0.24)
9 °C,12 °C	-0.0110	0.0109	-0.0180	-0.00870	0.0659	0.0404
	(-0.54)	(0.93)	(-0.95)	(-1.12)	(0.22)	(0.27)
15 °C,18 °C	0.0402	-0.0195	0.00578	-0.0104	-0.0722	-0.000592
	(1.59)	(-1.33)	(0.34)	(-1.58)	(-0.22)	(-0.00)
18 °C,21 °C	0.0505	-0.0399	0.00737	-0.0164	-0.474	0.0121
	(1.18)	(-1.60)	(0.29)	(-1.48)	(-1.13)	(0.05)
21 °C,24 °C	0.0416	-0.0422	-0.00211	-0.0139	-1.089*	0.136
	(0.77)	(-1.54)	(-0.07)	(-1.02)	(-2.11)	(0.48)
24 °C,27 °C	0.0427	-0.0659	0.00968	-0.0234	-1.669*	-0.135
	(0.68)	(-1.96)	(0.27)	(-1.51)	(-2.22)	(-0.44)
27 °C,30 °C	0.0805	-0.103*	0.0306	-0.0277	-1.560	-0.627
	(1.17)	(-2.58)	(0.73)	(-1.76)	(-1.74)	(-1.50)
30 °C 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 14: Estimates of the specification for week-end vs. weekdays for different types of income. All regressions include county and time fixed effects. Standard errors clustered by year. Stars indicate statistical significance at the 10 percent (*), 5 percent (**) and 1 percent (***) level.

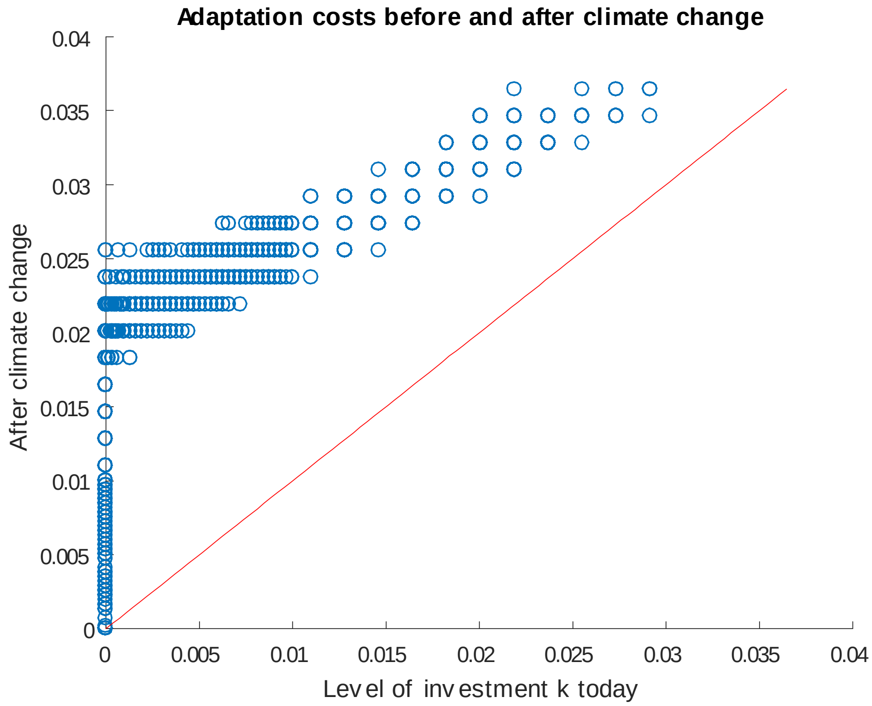

Figure 20: This figure plots the adaptation chosen by each county in the current climate (x-axis) against the adaptation it will choose after climate change (y-axis) according to the structural model.

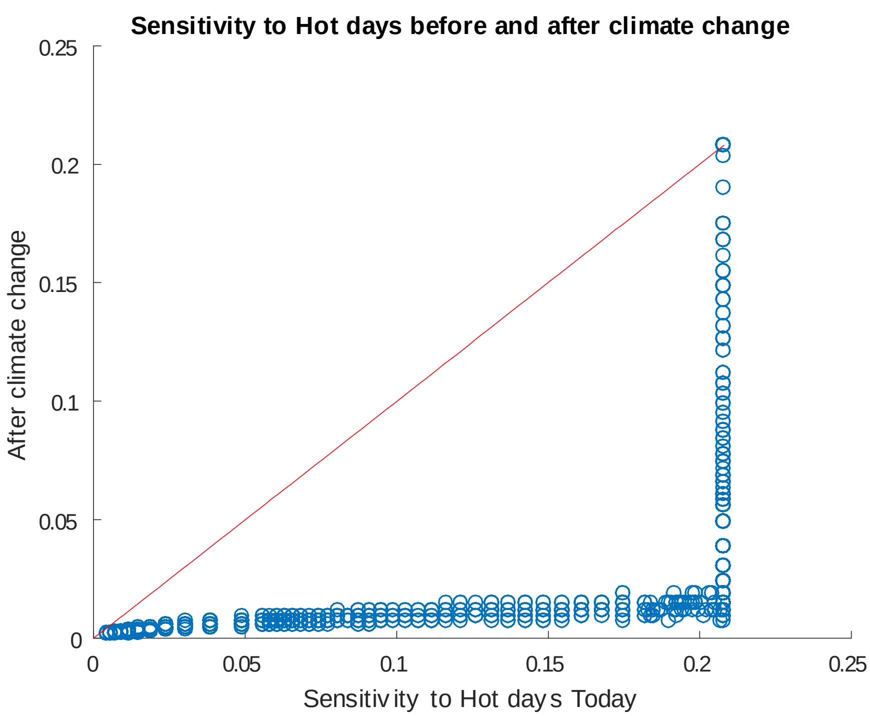

Figure 21: This figure plots the sensitivity to temperature of each county in the current climate (x-axis) against its sensitivity after climate change (y-axis) according to the structural model.