Online Appendix
Adaptation and the Cost of Rising Temperature for the U.S. economy

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Section 2 of this appendix presents additional results for the reduced form results (corresponding to Section 2 of the paper). Section 3 discusses extrapolation (summarized in section 4.3 of the paper). Section 4 presents additional results for the structural model of adaptation (corresponding to Sections 3 and 4 of the paper).

2 Reduced-form Results

2.1 Summary Statistics and Average Sensitivity of Income to Temperature

Table 1 presents summary statistics for our data. Figure 1 depicts the coefficient estimates β_k of equation (1) in the text of the paper, restated here for convenience:

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

The central bin (12°C-15°C) is omitted, providing a reference by which the impact of temperature deviations are evaluated. The bars indicate 95% confidence intervals, constructed using double-clustered standard errors (by county and NOAA region-year). The x-axis spans the set of temperature bins, and the y-axis measures the estimated percentage change (log change) in per capita personal income in response to an additional day in a given temperature bin. The first column of table 2 prints out these same parameter estimates.[1]

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[1]Our estimates are quite close to those of the paper by Deryugina and Hsiang (2014), even though our specification is slightly different (in first difference rather than in level with a lagged dependent variable). Hence, we confirm their results. Our standard errors are somewhat larger because we double cluster by county and NOAA region-year rather

Table 3 presents some variants on this basic regression: column 2 is a weighted regression; the estimated effects are smaller in this case. Column 3 removes the time fixed effects, leading to larger standard errors but similar point estimates than the baseline. Column 4 shows the results if we use the change in bin (i.e., bin minus bin of last year) to measure the temperature shock. This leads to similar results. Columns (5) and (6) include a lag, i.e. estimate the following equation:

$$\Delta \log Y_{i,t} = \alpha_i + \delta_t + \sum_{k=1}^{K} \beta_k Bin_{k,i,t} + \sum_{k=1}^{K} \gamma_k Bin_{k,i,t-1} + \varepsilon_{i,t}, \tag{2}$$

The coefficients γ_k are plotted in figure 2. As can be seen, the point estimates on the lagged bins (γ_k) are close to the opposite of the estimates on the current bins (β_k), suggesting that the effect of the bad weather is largely made up over the following year (but there does not appear to be an overshoot). Finally, column 7 shows that the results are largely unchanged if we also include controls for precipitation.

2.2 Heterogeneity in Sensitivity to Temperature

In the interest of clarity and brevity, the main body of the paper uses a single approach to document the heterogeneity in sensitivity to temperature, namely the interaction model (equation (2) of the paper). In this section we provide additional evidence to support our claim that there is a large heterogeneity, and that the major factor driving this heterogeneity is climate. We also provide more robustness analysis on the interaction models.

The first additional piece of evidence comes from simple sample splits. Columns 2 through 6 of table 2 report the estimates from equation 1 for five subsamples, defined as the quintiles of long-run average temperature (the simple average of daily temperature over our entire sample). The coefficients on the top two bins (days falling in the 27°C - 30°C and 30°C+ range) decrease markedly in absolute value as we go from first quintile to the fifth quintile. The same pattern holds when we define the quintiles based on the average number of hot days rather than the average temperature; this is shown in table 4. (This is the evidence we use to estimate the model.)

The second additional piece of evidence in favor of heterogeneity, is based on estimating a sensitivity to hot days for each county separately from a pure time-series regression. Specifically, we estimate:

$$\Delta \log Y_{i,t} = \alpha_i + \beta_i HD_{i,t} + \varepsilon_{i,t}, \tag{3}$$

and in figure 3 we plot the estimated β_i against the average annual number of hot days in the county (in log). Of course, each coefficient β_i is estimated using a single time series regression with 36 points at most, and hence they are fairly noisy, especially when we don't have many hot days (the left side of the graph). But the association is remarkably strong overall. The same pattern holds if we use "very hot days" (i.e., 30°C+) instead of "hot days" (27°C+); see figure 4.

than by county and year.

	Mean	Std.Dev.	Min	p5	Median	p95	Max	Count
Days in Range								
-15°C or less	4.16	8.53	0.00	0.00	0.00	23.00	80.22	65537
-15°C,-12°C	3.45	4.94	0.00	0.00	1.00	14.00	36.00	65537
-12°C,-9°C	5.53	6.55	0.00	0.00	3.00	19.00	43.00	65537
-9°C,-6°C	8.62	8.53	0.00	0.00	6.98	24.00	59.00	65537
-6°C,-3°C	13.07	10.72	0.00	0.00	12.03	31.00	63.00	65537
-3°C,0°C	18.36	12.68	0.00	0.00	19.00	39.00	84.00	65537
0°C,3°C	25.26	13.91	0.00	1.00	26.00	48.00	104.00	65537
3°C,6°C	29.11	12.89	0.00	6.00	29.00	50.00	112.00	65537
6°C,9°C	31.02	11.81	0.00	15.00	30.00	50.00	117.00	65537
9°C,12°C	32.45	10.86	0.00	19.00	31.00	50.00	134.00	65537
12°C,15°C	32.63	10.95	0.00	19.95	31.00	49.00	216.41	65537
15°C,18°C	36.06	10.12	0.00	22.94	35.00	52.00	160.56	65537
18°C,21°C	38.00	11.07	0.00	21.06	38.00	55.15	134.00	65537
21°C,24°C	35.96	15.75	0.00	5.00	37.00	59.84	126.00	65537
24°C,27°C	30.48	24.32	0.00	0.00	28.00	73.00	153.00	65537
27°C,30°C	17.34	24.14	0.00	0.00	5.98	69.81	170.00	65537
30°C or more	3.49	10.30	0.00	0.00	0.00	20.00	131.00	65537
In Log Differences								
Personal Income P.C.	5.57	5.64	-100.83	-2.01	5.15	13.98	88.43	65537
Wages and Salaries	5.90	6.05	-103.25	-2.41	5.51	15.13	189.18	65537
Proprietor Income	5.06	26.56	-540.26	-31.24	5.45	40.26	541.10	65383
In Thousands								
Population	138.99	388.09	2.00	6.00	37.00	609.00	10170.00	65537

Table 1: Summary statistics for the series used in our analysis. Source: Bureau of Economic Analysis (B.E.A.) and U.S.-HCN.

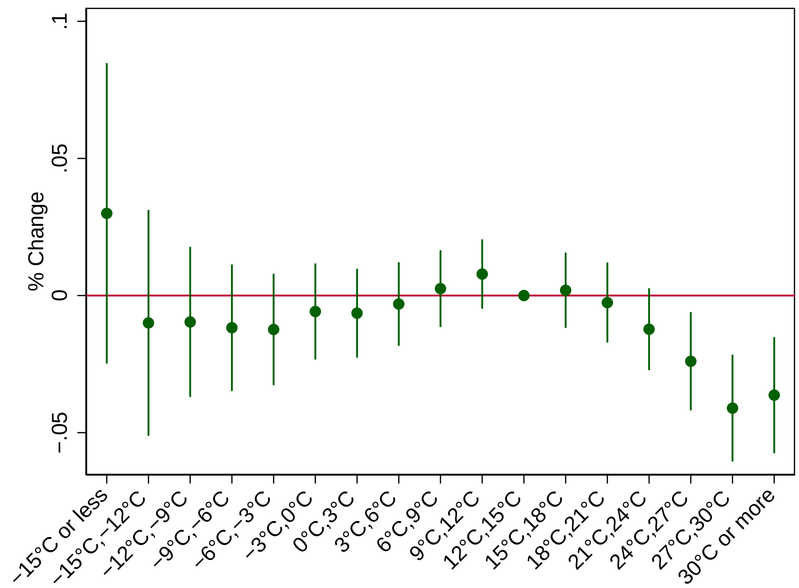

Figure 1: Estimated coefficients β_k from equation 1 and 95% confidence intervals (double-clustered by county and NOAA region-year).

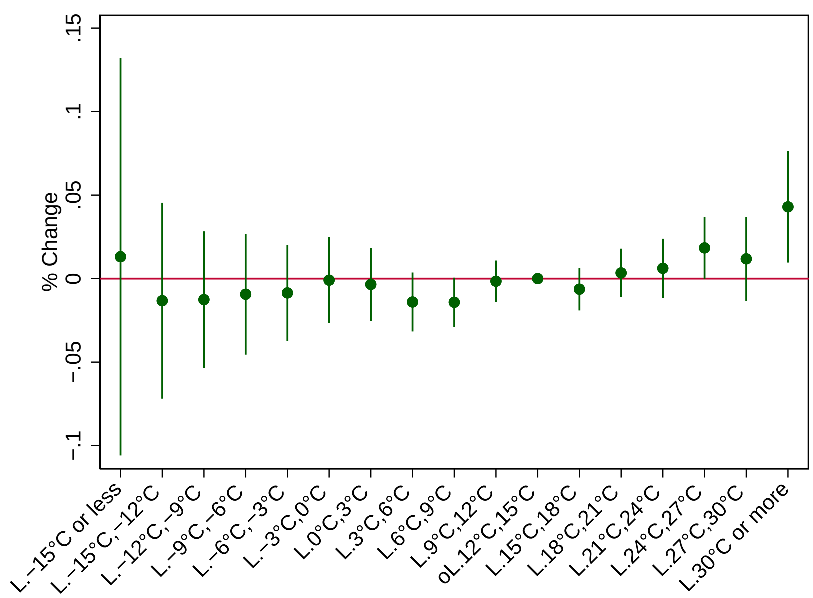

Figure 2: Estimated coefficients γ_k from equation 2 (i.e. lagged effects of temperature) and 95% confidence intervals (double-clustered by county and NOAA region-year).

	Baseline	Quintile 1	Quintile 2	Quintile 3	Quintile 4	Quintile 5
-15°C or less	0.030	0.020	0.043	0.029	-0.157	-0.337
	(0.028)	(0.035)	(0.032)	(0.050)	(0.144)	(0.549)
-15°C,-12°C	-0.010	-0.079**	0.022	0.038	0.128	-0.531
	(0.021)	(0.029)	(0.032)	(0.041)	(0.074)	(0.271)
-12°C,-9°C	-0.010	-0.061*	0.006	0.014	0.026	0.331
	(0.014)	(0.027)	(0.022)	(0.025)	(0.060)	(0.184)
-9°C,-6°C	-0.012	-0.029	-0.020	-0.020	-0.002	0.104
	(0.012)	(0.020)	(0.019)	(0.023)	(0.031)	(0.104)
-6°C,-3°C	-0.012	-0.045*	-0.016	0.003	-0.048	-0.057
	(0.010)	(0.020)	(0.016)	(0.018)	(0.030)	(0.059)
-3°C,0°C	-0.006	-0.054**	-0.006	0.003	0.014	-0.052*
	(0.009)	(0.018)	(0.015)	(0.015)	(0.020)	(0.026)
0°C,3°C	-0.006	-0.025	-0.008	-0.018	0.019	-0.002
	(0.008)	(0.021)	(0.013)	(0.013)	(0.018)	(0.017)
3°C,6°C	-0.003	-0.008	0.008	-0.016	0.008	0.003
	(0.008)	(0.019)	(0.015)	(0.012)	(0.015)	(0.013)
6°C,9°C	0.003	-0.008	0.013	0.006	-0.010	0.001
	(0.007)	(0.018)	(0.016)	(0.013)	(0.012)	(0.013)
9°C,12°C	0.008	-0.004	0.004	0.005	0.017	0.004
	(0.006)	(0.018)	(0.014)	(0.011)	(0.012)	(0.010)
15°C,18°C	0.002	-0.001	0.030*	-0.002	-0.005	-0.003
	(0.007)	(0.016)	(0.014)	(0.011)	(0.013)	(0.011)
18°C,21°C	-0.003	-0.044*	0.000	0.011	0.011	0.011
	(0.007)	(0.018)	(0.014)	(0.012)	(0.014)	(0.011)
21°C,24°C	-0.012	-0.025	-0.023	-0.027*	0.005	0.004
	(0.008)	(0.020)	(0.013)	(0.012)	(0.013)	(0.009)
24°C,27°C	-0.024**	-0.071*	0.028	-0.005	0.001	0.011
	(0.009)	(0.029)	(0.019)	(0.012)	(0.014)	(0.010)
27°C,30°C	-0.041***	-0.210*	-0.115**	-0.043*	-0.019	-0.000
	(0.010)	(0.093)	(0.038)	(0.021)	(0.015)	(0.010)
30°C or more	-0.036***	-0.271	-0.492***	-0.252***	0.001	0.011
	(0.011)	(0.223)	(0.140)	(0.044)	(0.019)	(0.011)
Observations	65537	13133	13104	13122	13106	13072

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2: Coefficients and standard errors for the baseline regression (equation 1) and sub-sample analysis by quintile of counties sorted on long-run average temperature (coldest (1) to hottest (5)).

	Baseline	Pop Wt	No Time FE	Δ Bins	W Lags	W Lags	W Prcp.
-15°C or less	0.030	0.008	0.106**	-0.016	0.032	0.013	0.030
	(0.028)	(0.015)	(0.040)	(0.044)	(0.030)	(0.039)	(0.028)
-15°C,-12°C	-0.010	-0.011	0.037	-0.016	-0.013	-0.013	-0.010
	(0.021)	(0.014)	(0.035)	(0.025)	(0.021)	(0.024)	(0.021)
-12°C,-9°C	-0.010	0.001	0.021	-0.013	-0.008	-0.013	-0.009
	(0.014)	(0.011)	(0.025)	(0.019)	(0.015)	(0.017)	(0.014)
-9°C,-6°C	-0.012	-0.006	-0.016	-0.010	-0.005	-0.009	-0.011
	(0.012)	(0.009)	(0.021)	(0.015)	(0.012)	(0.014)	(0.012)
-6°C,-3°C	-0.012	-0.014	-0.009	-0.014	-0.006	-0.009	-0.012
	(0.010)	(0.008)	(0.019)	(0.014)	(0.011)	(0.012)	(0.010)
-3°C,0°C	-0.006	-0.003	-0.002	-0.012	-0.008	-0.001	-0.006
	(0.009)	(0.008)	(0.018)	(0.014)	(0.010)	(0.011)	(0.009)
0°C,3°C	-0.006	-0.006	0.001	-0.009	-0.005	-0.003	-0.007
	(0.008)	(0.006)	(0.017)	(0.012)	(0.009)	(0.009)	(0.008)
3°C,6°C	-0.003	-0.005	-0.012	-0.002	-0.002	-0.014	-0.003
	(0.008)	(0.005)	(0.015)	(0.011)	(0.008)	(0.009)	(0.008)
6°C,9°C	0.003	-0.011*	-0.003	0.003	0.001	-0.014*	0.002
	(0.007)	(0.005)	(0.013)	(0.009)	(0.007)	(0.007)	(0.007)
9°C,12°C	0.008	0.000	0.015	0.007	0.007	-0.002	0.007
	(0.006)	(0.008)	(0.010)	(0.007)	(0.007)	(0.006)	(0.006)
15°C,18°C	0.002	-0.008	0.011	0.003	0.001	-0.006	0.003
	(0.007)	(0.005)	(0.011)	(0.008)	(0.007)	(0.007)	(0.007)
18°C,21°C	-0.003	-0.006	-0.003	0.001	-0.007	0.003	-0.003
	(0.007)	(0.005)	(0.013)	(0.009)	(0.007)	(0.007)	(0.007)
21°C,24°C	-0.012	-0.012*	-0.002	-0.004	-0.014	0.006	-0.012
	(0.008)	(0.006)	(0.013)	(0.009)	(0.008)	(0.008)	(0.008)
24°C,27°C	-0.024**	-0.014**	-0.007	-0.022*	-0.028**	0.018*	-0.024**
	(0.009)	(0.005)	(0.017)	(0.010)	(0.010)	(0.009)	(0.009)
27°C,30°C	-0.041***	-0.011	-0.052**	-0.036**	-0.047***	0.012	-0.042***
	(0.010)	(0.007)	(0.018)	(0.014)	(0.011)	(0.010)	(0.010)
30°C or more	-0.036***	-0.004	-0.045	-0.044	-0.044***	0.043***	-0.038***
	(0.011)	(0.009)	(0.023)	(0.023)	(0.012)	(0.012)	(0.011)
Observations	65537	65537	65537	57812	57812	57812	64493

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3: Coefficients and standard errors for the baseline equation 1 (column 1), and some variants: weighted regression (column 2), no time effects (column 3), bins in first-difference (column 4), regression including lags (columns 5-6, corresponding to equation 2), and including precipitation controls (column 7).

	Baseline	Quintile 1	Quintile 2	Quintile 3	Quintile 4	Quintile 5
-15°C or less	0.030	0.020	0.043	0.029	-0.157	-0.337
	(0.028)	(0.035)	(0.032)	(0.050)	(0.144)	(0.549)
-15°C,-12°C	-0.010	-0.079**	0.022	0.038	0.128	-0.531
	(0.021)	(0.029)	(0.032)	(0.041)	(0.074)	(0.271)
-12°C,-9°C	-0.010	-0.061*	0.006	0.014	0.026	0.331
	(0.014)	(0.027)	(0.022)	(0.025)	(0.060)	(0.184)
-9°C,-6°C	-0.012	-0.029	-0.020	-0.020	-0.002	0.104
	(0.012)	(0.020)	(0.019)	(0.023)	(0.031)	(0.104)
-6°C,-3°C	-0.012	-0.045*	-0.016	0.003	-0.048	-0.057
	(0.010)	(0.020)	(0.016)	(0.018)	(0.030)	(0.059)
-3°C,0°C	-0.006	-0.054**	-0.006	0.003	0.014	-0.052*
	(0.009)	(0.018)	(0.015)	(0.015)	(0.020)	(0.026)
0°C,3°C	-0.006	-0.025	-0.008	-0.018	0.019	-0.002
	(0.008)	(0.021)	(0.013)	(0.013)	(0.018)	(0.017)
3°C,6°C	-0.003	-0.008	0.008	-0.016	0.008	0.003
	(0.008)	(0.019)	(0.015)	(0.012)	(0.015)	(0.013)
6°C,9°C	0.003	-0.008	0.013	0.006	-0.010	0.001
	(0.007)	(0.018)	(0.016)	(0.013)	(0.012)	(0.013)
9°C,12°C	0.008	-0.004	0.004	0.005	0.017	0.004
	(0.006)	(0.018)	(0.014)	(0.011)	(0.012)	(0.010)
15°C,18°C	0.002	-0.001	0.030*	-0.002	-0.005	-0.003
	(0.007)	(0.016)	(0.014)	(0.011)	(0.013)	(0.011)
18°C,21°C	-0.003	-0.044*	0.000	0.011	0.011	0.011
	(0.007)	(0.018)	(0.014)	(0.012)	(0.014)	(0.011)
21°C,24°C	-0.012	-0.025	-0.023	-0.027*	0.005	0.004
	(0.008)	(0.020)	(0.013)	(0.012)	(0.013)	(0.009)
24°C,27°C	-0.024**	-0.071*	0.028	-0.005	0.001	0.011
	(0.009)	(0.029)	(0.019)	(0.012)	(0.014)	(0.010)
27°C,30°C	-0.041***	-0.210*	-0.115**	-0.043*	-0.019	-0.000
	(0.010)	(0.093)	(0.038)	(0.021)	(0.015)	(0.010)
30°C or more	-0.036***	-0.271	-0.492***	-0.252***	0.001	0.011
	(0.011)	(0.223)	(0.140)	(0.044)	(0.019)	(0.011)
Observations	65537	13133	13104	13122	13106	13072

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4: Coefficients and standard errors for the baseline regression (equation 1) and sub-sample analysis by quintile of counties sorted on average number of hot days per year (smallest (1) to largest (5)).

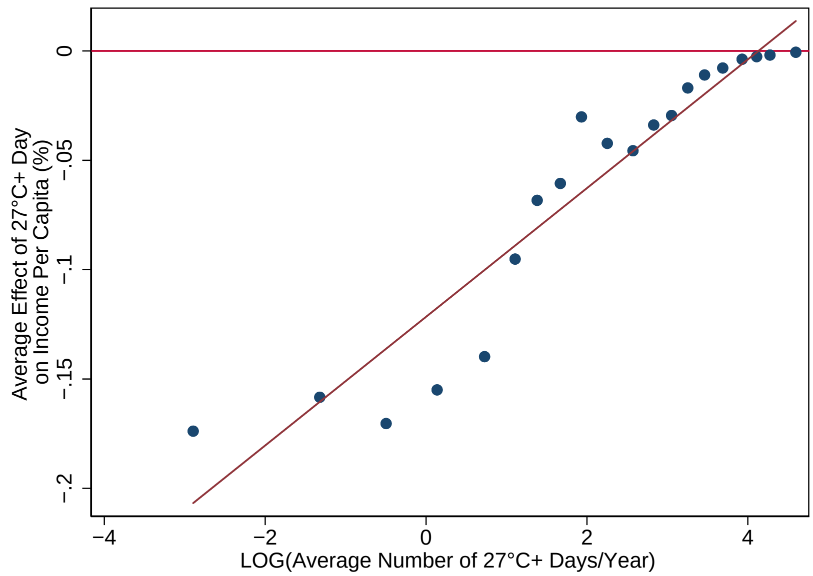

Figure 3: This figure plots the county-specific slope coefficient from equation 3 estimated using hot days (27°C+) against the log of the average number of hot days in the county. Binscatter with 20 bins.

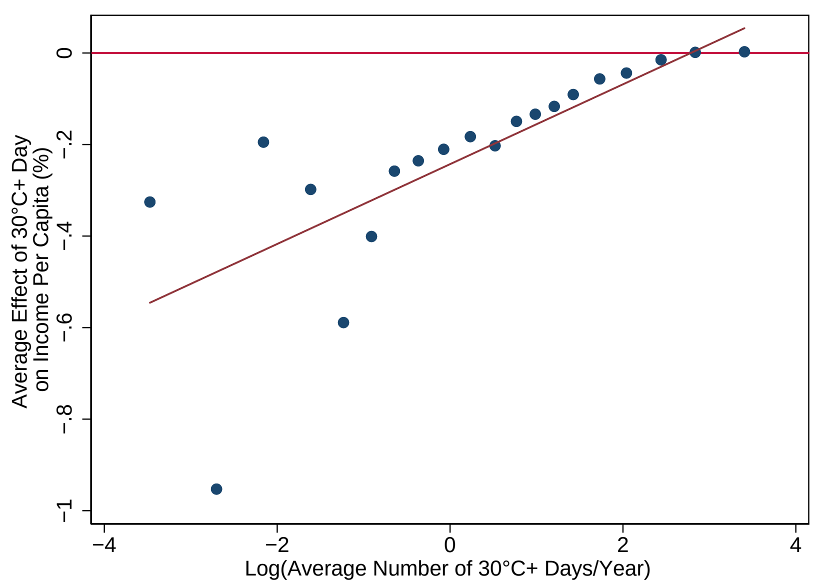

Figure 4: This figure plots the county-specific slope coefficient from equation 3 estimated using very hot days (30°C+) against the log of the average number of very hot days in the county. Binscatter with 20 bins.

We now turn to the interaction models. These models take the form of equation (2) of the paper, restated here for convenience:

$$\Delta \log Y_{i,t} = \alpha_i + \delta_t + \sum_{k=1}^{K} \left(\sum_{l=0}^{L} \beta_{kl} x_{il} \right) Bin_{k,i,t} + \varepsilon_{i,t}. \tag{4}$$

First, table 5 presents the coefficient estimates and standard errors for the model estimated in section 2 of the paper, which results are displayed only graphically in the main body of the paper (in figure 1 of the paper). The main takeaway from this table is that the coefficients on average temperature are significant, in particular the quadratic term, and these coefficients are stable as we add additional covariates. Moreover, the other covariates appear less important statistically (and economically as shown in figure 1 of the paper), and once they are put together (e.g. in column F), the coefficient size of the additional covariates falls, and their statistical significance shrinks: climate variable tend to "drive out" the non-climate variables.

Second, table 6 shows the results if we focus on "very hot days" (i.e. 30°C+) rather than merely "hot days" (i.e. 27°C+).[2] The results are quite similar and possibly even stronger: the coefficients on the quadratic in long-run temperature are stable across specifications, and tend to drive out the effect of population. Figure 5 provides the depiction of marginal effects similar to figure 1 in the paper, for this specification.

Third, in table 7 and figure 6 we change the definition of climate variable, and, rather than using the long-run average of daily temperature, we use the (log) average number of very hot days per year. The results are again quite similar. (Here, given the log specification, there is no need for a quadratic or cubic specification.)

[2]That is, we change the definition of hot days (the top bin) that is interacted with the climate variables and/or the other covariates.

	A	B	C	D	E	F	G	H	I
avg temperature	0.87***	4.35**	9.52	5.38**	3.86*	4.74**			
	(0.22)	(1.63)	(8.11)	(1.64)	(1.53)	(1.57)			
avg temperature^2		-0.11*	-0.40	-0.14**	-0.10*	-0.12*			
		(0.05)	(0.51)	(0.05)	(0.05)	(0.05)			
avg temperature^3			0.01						
			(0.01)						
avg rel. PC income				6.30**		2.28		-1.93	
				(2.23)		(3.23)		(12.68)	
average farming share					-11.47	6.31			-123.00**
					(35.77)	(35.49)			(42.51)
log avg rel. pop.						1.03*	1.01**		
						(0.49)	(0.37)		
log avg rel. pop.^{2}							-0.46		
							(0.30)		
avg rel. PC income^2								4.43	
								(11.13)	
average farming share^2									504.78**
									(184.65)
Observations	65537	65537	65537	65537	65537	65537	65537	65537	65537

Coefficients are multiplied by 100 for readability

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5: The table reports the coefficients β_{KI} (from equation 4) i.e. the coefficient on the covariates interacted with the top temperature bin. The top temperature bin is defined here as 27°C plus ("hot days"). Each column corresponds to one of the panels from Figure 1 of the paper. In columns A to C, the only covariate is the county's long run average temperature (in a linear, quadratic, or cubic specification). In columns D-E we add additional covariates (income, farming share, or both of them pluss population) on top of the quadratic. In columns G-I we consider these covariates without the quadratic in long-run average temperature. Standard errors are double clustered by county and NOAA-year.

	A	B	C	D	E	F	G	H	I
avg temperature	1.30***	10.17***	43.94**	10.36***	8.63**	8.49**			
	(0.38)	(2.84)	(14.04)	(2.86)	(2.75)	(2.82)			
avg temperature^2		-0.25**	-2.25**	-0.26**	-0.22**	-0.21**			
		(0.08)	(0.83)	(0.08)	(0.08)	(0.08)			
avg temperature^3			0.04*						
			(0.02)						
avg rel. PC income				9.12**		6.10		-33.66	
				(3.37)		(5.24)		(17.34)	
average farming share					-45.31	-36.46			-158.78*
					(49.79)	(48.49)			(69.71)
log avg rel. pop.						0.16	1.13*		
						(0.68)	(0.51)		
log avg rel. pop.^{2}							-0.37		
							(0.39)		
avg rel. PC income^2								41.22*	
								(16.87)	
average farming share^2									565.48
									(349.95)
Observations	65537	65537	65537	65537	65537	65537	65537	65537	65537

Coefficients are multiplied by 100 for readability

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 6: The table reports the coefficients β_{KI} (from equation 4) i.e. the coefficient on the covariates interacted with the top temperature bin. The top temperature bin is defined here as 30°C plus ("very hot days"). Each column corresponds to one of the panels from Figure 1 of the paper. In columns A to C, the only covariate is the county's long run average temperature (in a linear, quadratic, or cubic specification). In columns D-E we add additional covariates (income, farming share, or both of them pluss population) on top of the quadratic. In columns G-I we consider these covariates without the quadratic in long-run average temperature. Standard errors are double clustered by county and NOAA-year.

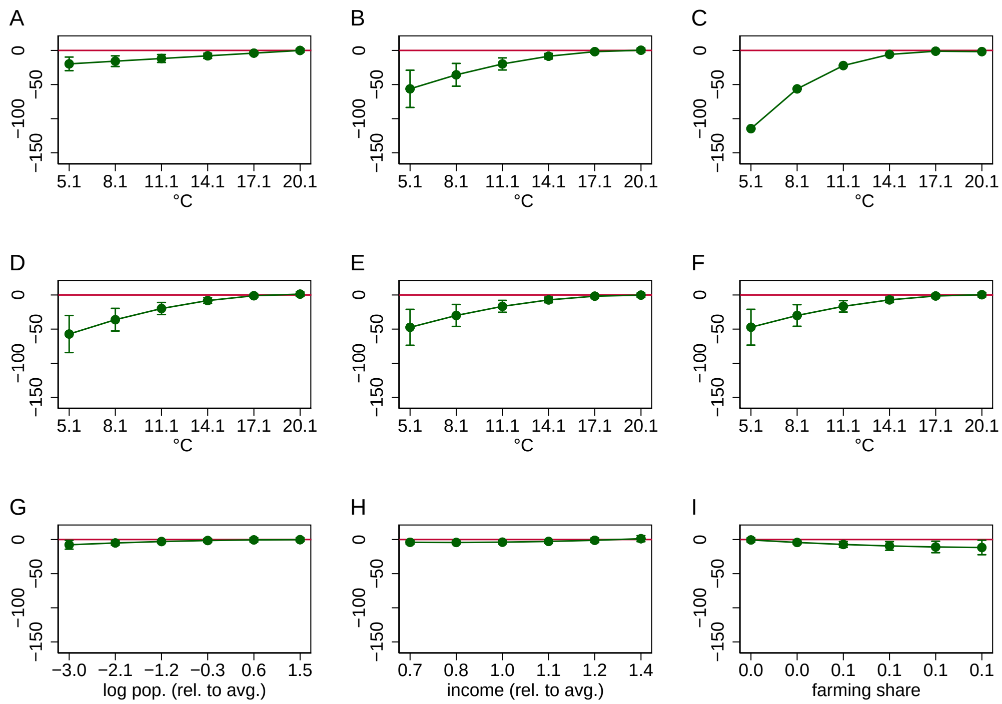

Figure 5: Marginal effect of a day above 30°C on annual income, as a function of the county's average temperature (panels A-F) or some other characteristic (panels G-I).

Note: The figure depicts the estimated marginal effect of an additional day in the 30°C plus bin, for different models of equation 4, together with plus and minus two standard error bands (double-clustered by county and by NOAA region-year). Panels A-F plot the marginal effect as a function of average temperature, while panels G-I plot it as a function of some other county characteristics. In each case, the x-axis ranges from the 5th percentile to the 95th percentile of the distribution of the variable. Panel A: interaction is linear in average temperature; panel B: quadratic in average temperature; Panel C: cubic in average temperature (S.E. omitted for readability); Panel D: quadratic in average temperature, plus average income (relative to national); Panel E: quadratic in average temperature, plus average farming share; Panel F: quadratic in average temperature, plus average population (in log, relative to national), average income (relative to national), and average farming share; Panel G: quadratic in average population (in log, relative to national) ; Panel H: quadratic in average income (relative to national); Panel I: quadratic in average farming share.

	A	B	C	D	E	F	G
log avg annual very hot days	4.65***	4.98***	4.05***	4.38***			
	(0.82)	(0.82)	(0.79)	(0.87)			
avg rel. PC income		8.72*		4.51		-33.66	
		(3.40)		(5.67)		(17.34)	
average farming share			-66.47	-55.76			-158.78*
			(52.33)	(49.41)			(69.71)
log avg rel. pop.				0.40	1.13*		
				(0.74)	(0.51)		
log avg rel. pop.^{2}					-0.37		
					(0.39)		
avg rel. PC income^2						41.22*	
						(16.87)	
average farming share^2							565.48
							(349.95)
Observations	47249	47249	47249	47249	65537	65537	65537

Coefficients are multiplied by 100 for readability

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 7: The table reports the coefficients β_{Kl} (equation 4) on the covariates interacted with the top temperature bin, defined as "very hot days" here i.e. 30°C plus, together with the associated standard errors. Each column corresponds to one interaction model, with different sets of covariates. In column A, the only covariate is the county's log of the average number of very hot days. In columns B-D we add additional covariates (income, farming share, or log population) on top of the quadratic. In columns E-G we consider these covariates without the log average number of hot days. Standard errors are double clustered by county and NOAA-year.

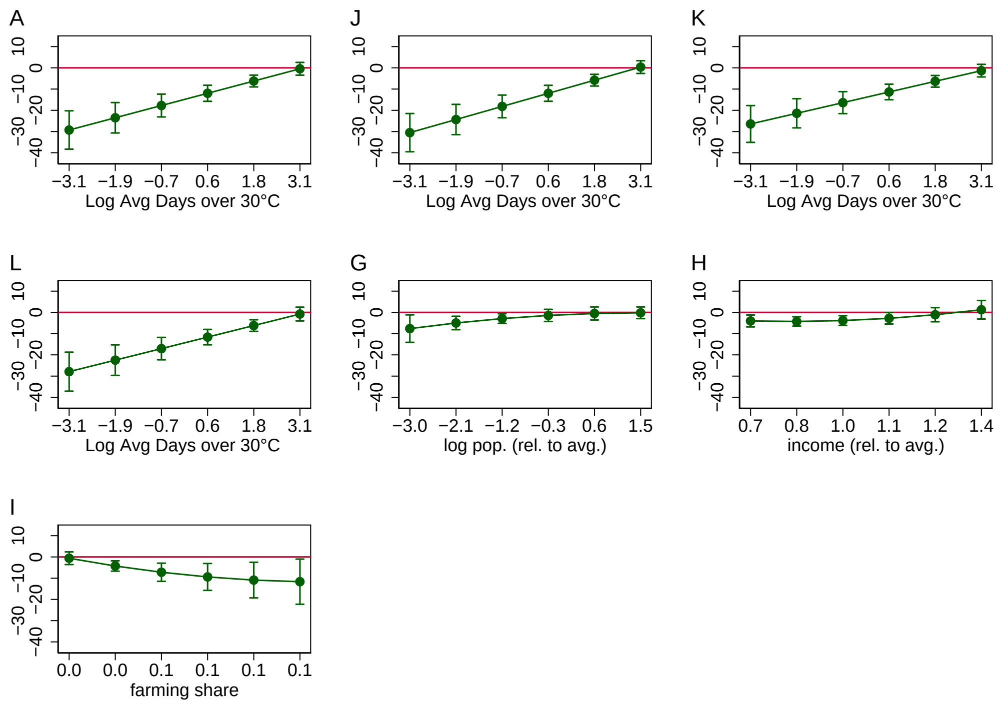

Figure 6: Marginal effect of a day above 30°C on annual income, as a function of the county's average temperature (panels A-F) or some other characteristic (panels G-I).

Note: The figure depicts the estimated marginal effect of an additional day in the 30°C plus bin, for different models of equation 4, together with plus and minus two standard error bands (double-clustered by county and by NOAA region-year). Panels A, J, K and L depict the marginal effect as a function of the (log) average annual number of very hot days in the county, while panels G-I plot it as a function of some other county characteristic. Panel A: interaction is linear in log average number of very hot days; Panel J: same as A, plus average income (relative to national); Panel K: same as A, plus average farming share; Panel L: same as A, plus average population (in log, relative to national), average income (relative to national), and average farming share; Panel G: quadratic in average population (in log, relative to national) ; Panel H: quadratic in average income (relative to national); Panel I: quadratic in average farming share.

3 Extrapolation

We first discuss the intensive margin of adaptation, before discussing the extensive margin. The intensive margin refers to the fact that days hotter than what we observe today may occur after climate change, requiring us to extrapolate our results to estimate the losses. The extensive margin refers to the fact that the number of hot days per year may become larger than the number observed in any county today. This is relevant for the adaptation choice since adaptation is chosen based on the expected costs of hot days - their frequency and intensity. When the number of hot days goes above anything currently observed, we are relying on some extrapolation of the adaptation technology.

3.1 Intensive Margin

To evaluate the concern that our estimated cost of hot days is reliable for very hot temperature, we estimated our model using a slightly altered version of our baseline regression where, we both extend the range of bins into the right tail of the temperature distribution (previously top coded at 30°C+ now top coded at 34°C+) and narrow the range of bins for more precise identification within this extended range (previously bins of width 3°C, now bins of width 2°C). Figure 7 depicts the coefficients and 95% confidence intervals. (For the range of temperature below 24°C (not shown) the specification is the same as our baseline model and the coefficients are very similar.) The green dots show the full sample results. The scarcity of very high temperature means that standard errors become wider, but there is no acceleration of the decline of income for very high temperature. Indeed, on the contrary the green dots suggest a slowdown. Further data exploration reveals that these results are affected by some outliers - resource-extracting counties that had some years with very high income growth due to high commodity prices, despite high temperature. In orange, we report the results when we exclude counties with a large mining industry share. In that case again, standard errors are wide, but the point estimates agree with the linear specification of costs used in the paper - i.e., each degree above 26°C reduces output further linearly.

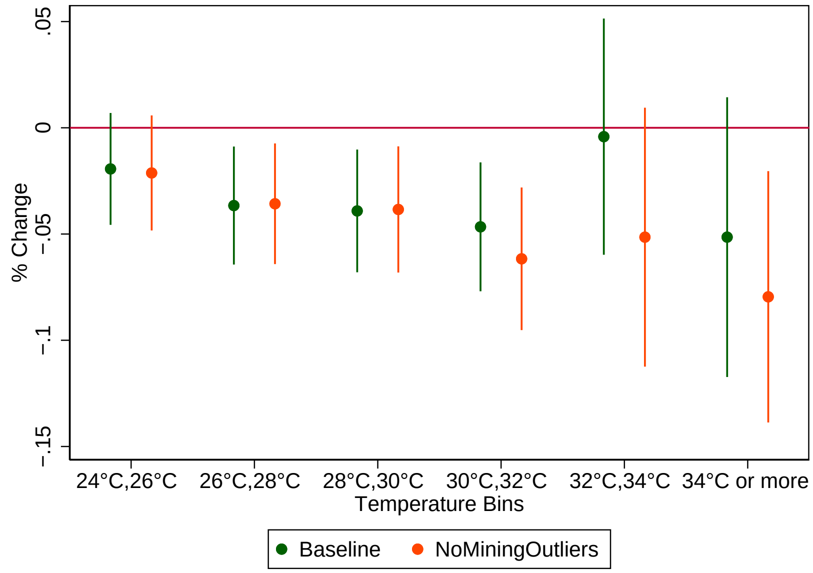

Figure 7: Intensive Margin Regression

3.2 Extensive Margin

To evaluate the concern about extrapolation at the extensive margin, figure 8 reports the distribution of hot days across counties in the current climate and after climate change (using the RCP 6.0 scenario).

Only 0.2% of counties (that is, 6 counties) have more hot days on average after climate change than the county with the maximum average number of hot days currently experiences. In this sense, we do not extrapolate dramatically, even for this fairly severe scenario. However, the increase in the extensive margin is more striking if we compare to the current 99th percentile rather than the max. The vertical red line shows the current 99th percentile. The number of counties with average annual hot days above this level after climate change is 8.5%, which is more significant. Table 8 reports this statistic for different scenarios and different percentiles.

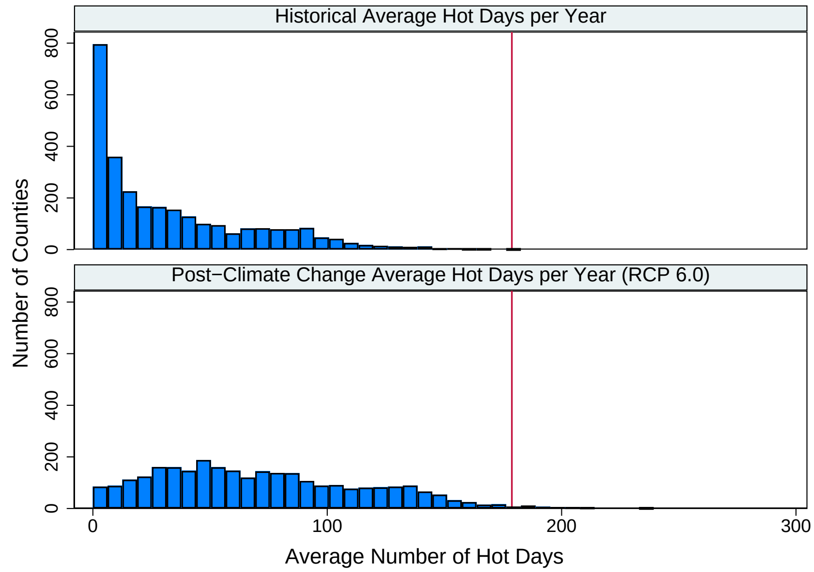

Figure 8: Histogram of the average number of hot days each year that a county experienced historically (top panel) and the projected histogram under the RCP 6.0 warming scenario from Rasmussen et al. (2016) (bottom panel). The red line shows the 99^{th} percentile of the the historical distribution.

Scenario	p95	p99	max
RCP 26	9.9	1.9	0.0
RCP 45	21.8	6.3	0.1
RCP 60	25.6	8.5	0.2
RCP 85	47.2	22.0	1.6

Table 8: The table reports, for each RCP scenario, the share of counties (in %) that have a number of hot days (27°C+) above the values observed in our data for the 95th percentile, the 99th percentile, an the maximum (across counties).

4 Additional structural model results

In this section we first present some additional results for the structural model of adaptation estimated in the paper, and then some variants of the model or estimation method.

First, table 9 presents statistics about climate change losses predicted by various model, similar to Table 3 in the paper, except that all statistics are now reported weighted (by the 2015 population) rather than unweighed. This tends to increase slightly both the median and the dispersion of losses.

Second, table 10 presents the correlation between the losses predicted by various models: the "uniform sensitivity" (also called "no adaptation", assumes the same adaptation for all counties, pre and post climate change), the "fixed adaptation" (assumes different adaptation across counties, but same pre and post climate change), and the "endogenous adaptation" model (for which we distinguish output and consumption, i.e. output less adaptation costs). The most striking feature from the table is the very weak (even negative) correlation between the losses predicted by the uniform sensitivity ("no adaptation") model and the other ones.

	Population Weighted					
	Median	Std.Dev.	p10	p25	p75	p90
Panel A: RCP 2.6						
Fixed adapt. C,Y	-0.94	0.53	-1.67	-1.35	-0.62	-0.41
Endogenous adapt. C	-0.84	0.40	-1.38	-1.09	-0.55	-0.38
Endogenous adapt. Y	0.13	1.49	-0.60	-0.42	2.23	3.26
Panel B: RCP 4.5						
Fixed adapt. C,Y	-2.32	1.21	-4.13	-3.30	-1.52	-1.16
Endogenous adapt. C	-1.59	0.59	-2.25	-1.96	-1.08	-0.84
Endogenous adapt. Y	0.09	1.55	-0.81	-0.61	2.22	3.25
Panel C: RCP 6.0						
Fixed adapt. C,Y	-2.97	1.48	-5.10	-4.03	-1.94	-1.46
Endogenous adapt. C	-1.89	0.66	-2.61	-2.29	-1.27	-1.01
Endogenous adapt. Y	0.08	1.58	-0.89	-0.65	2.21	3.25
Panel D: RCP 8.5						
Fixed adapt. C,Y	-6.46	2.85	-10.05	-8.67	-3.87	-2.72
Endogenous adapt. C	-2.79	0.82	-3.55	-3.36	-1.89	-1.53
Endogenous adapt. Y	0.04	1.62	-1.05	-0.77	2.20	3.23

Table 9: Same as Table 3 in the paper, but outcomes are now weighed by county population.

	NoAdaptC	Fixed Adapt C	Endogenous Adapt C	Endogenous Adapt Y
NoAdaptC	1.000			
Fixed Adapt C	0.092	1.000		
Endogenous Adapt C	-0.098	0.917	1.000	
Endogenous Adapt Y	-0.901	0.276	0.477	1.000

Table 10: Correlation of predicted outcomes for different RCP scenarios and different assumptions about adaptation.

Second, figure 9 depicts the adaptation spending k before and after climate change (left panel) and the resulting sensitivity to climate (right panel) together with the 45 degree line (in red).[3] Notably, all states are above the 45 degree line on the left panel, i.e. they all increase adaptation after climate change, and consequently they have lower sensitivity to climate change.

Third, Figure 4 in the main text depicts the predicted losses by region in RCP 6.0 scenario. Figures 10, 11 and 12 depict the predicted losses for the other three scenarios.

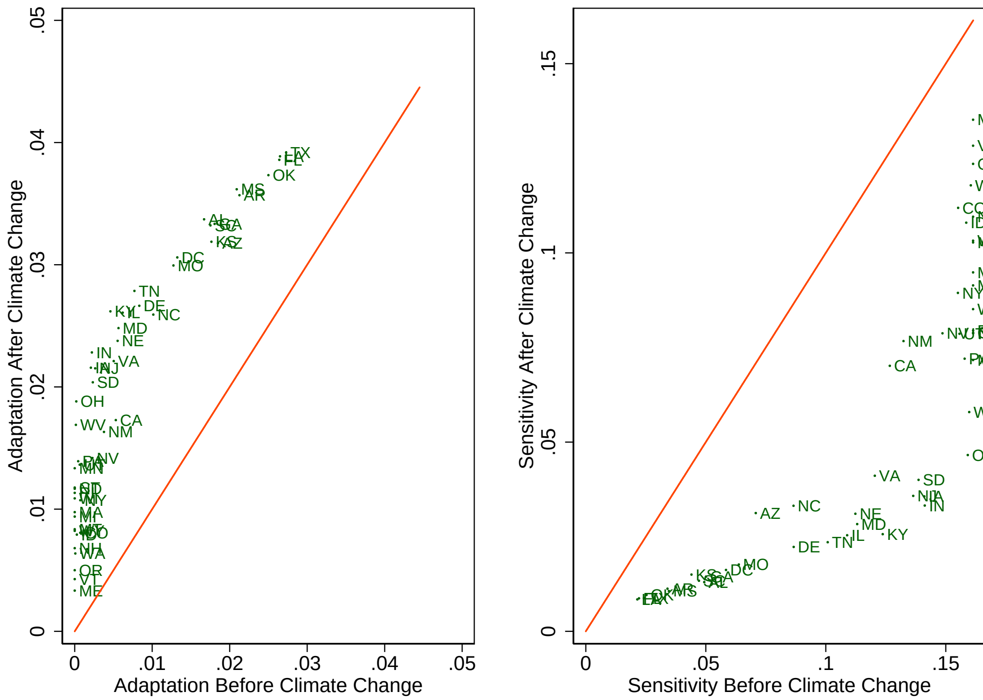

Figure 9: State Averages Before and After Climate Change: Adaptation (left); Sensitivity (right)

[3] We present states here rather than counties for easy readability; the state value is the simple average of the counties.

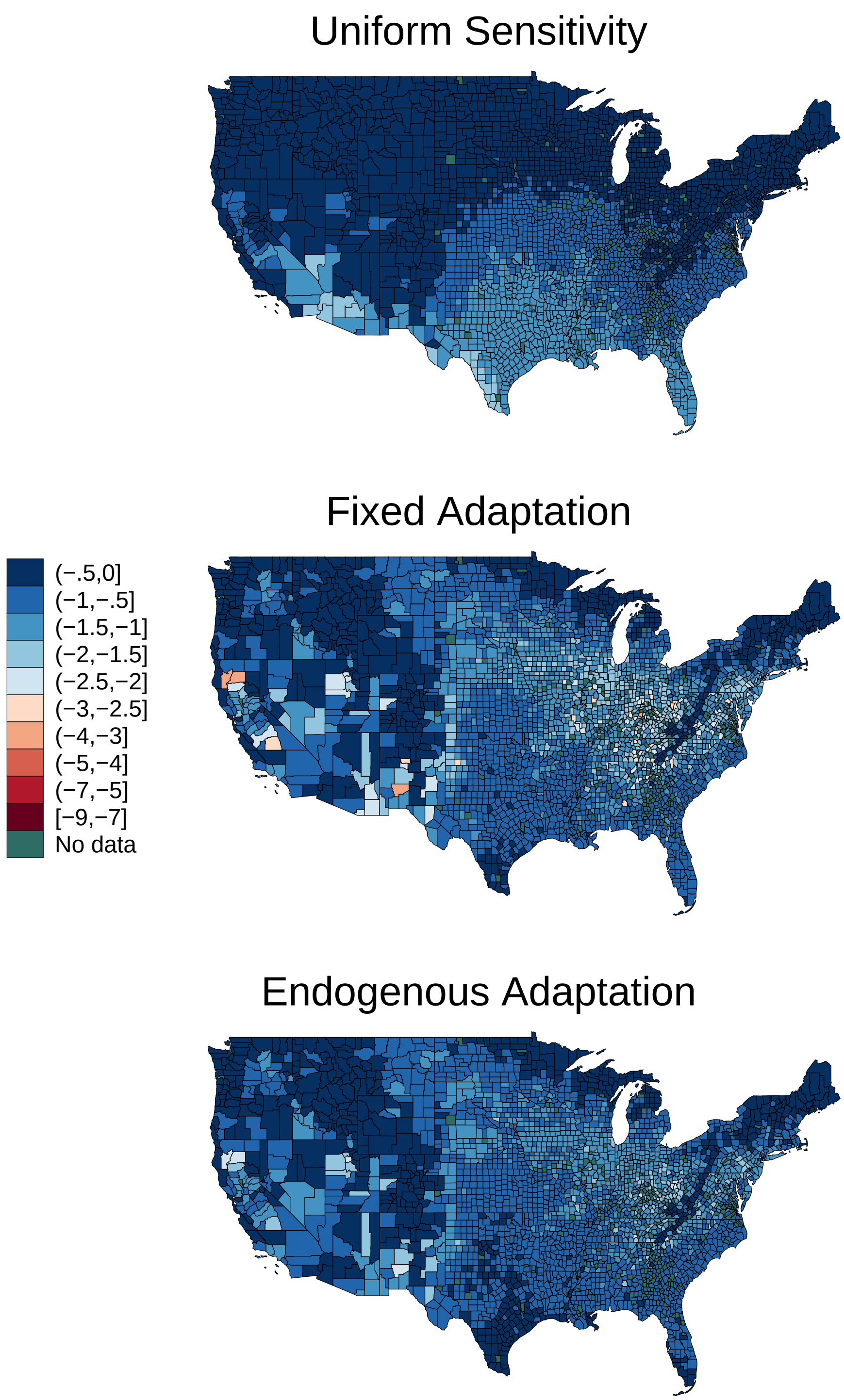

Figure 10: Predicted consumption losses for the RCP 2.6 scenario.

The figure displays the predicted decline in consumption (income net of adaptation costs) for each U.S. county in the RCP 2.6 scenario, for three different models. Top panel: uniform sensitivity; middle panel: fixed adaptation; bottom panel: endogenous adaptation.

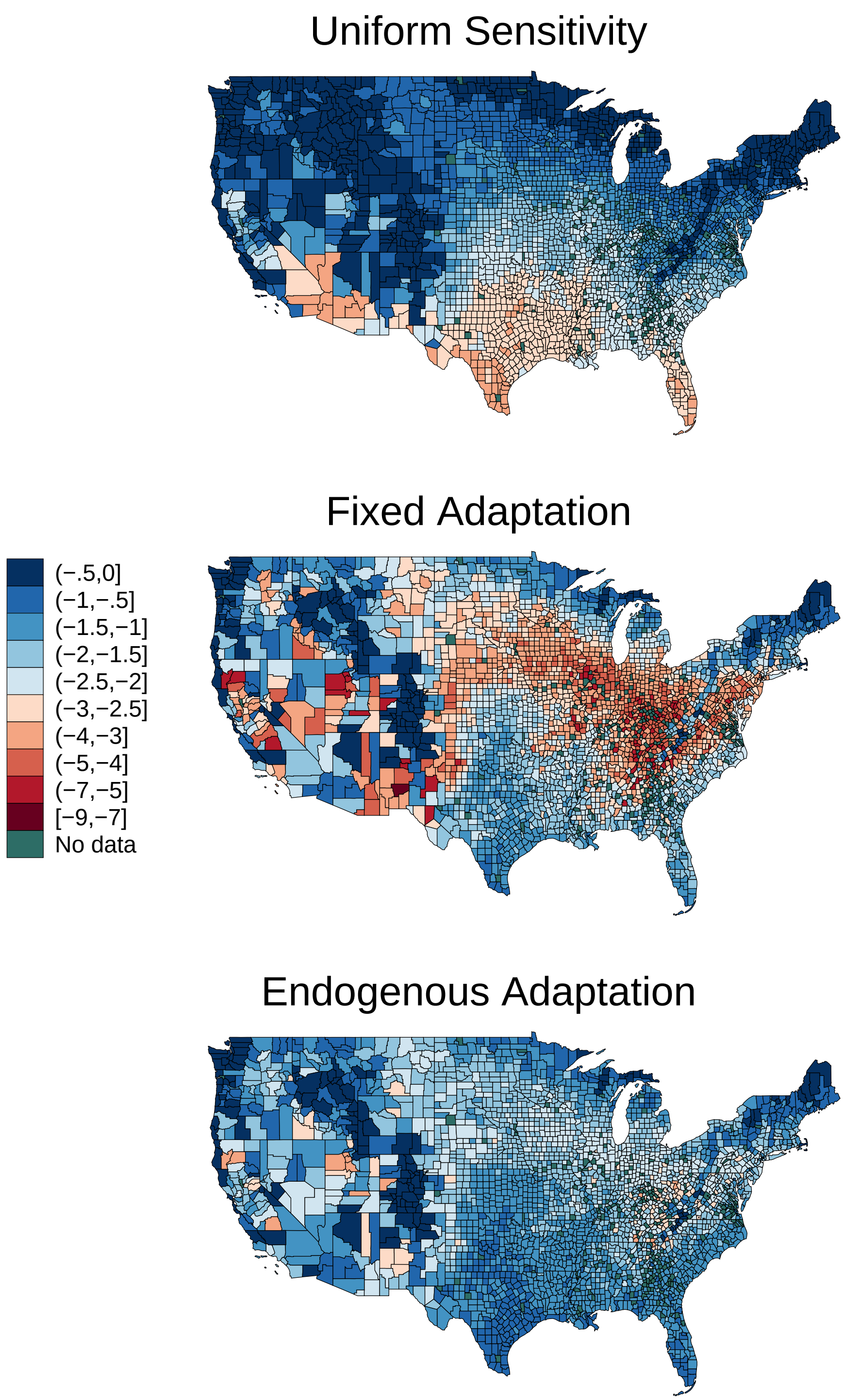

Figure 11: Predicted consumption losses for the RCP 4.5 scenario.

The figure displays the predicted decline in consumption (income net of adaptation costs) for each U.S. county in the RCP 4.5 scenario, for three different models. Top panel: uniform sensitivity; middle panel: fixed adaptation; bottom panel: endogenous adaptation.

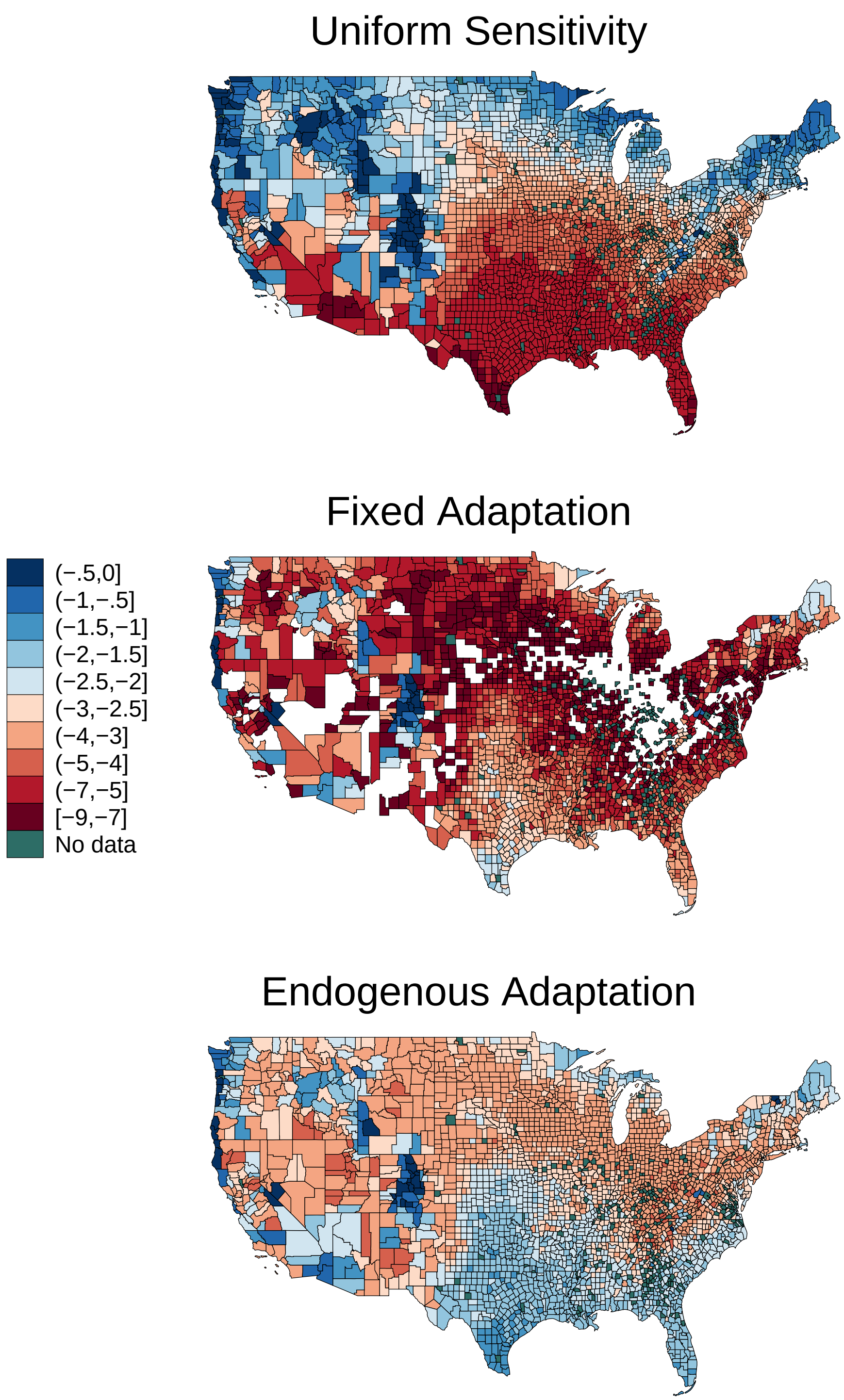

Figure 12: Predicted consumption losses for the RCP 8.5 scenario.

The figure displays the predicted decline in consumption (income net of adaptation costs) for each U.S. county in the RCP 8.5 scenario, for three different models. Top panel: uniform sensitivity; middle panel: fixed adaptation; bottom panel: endogenous adaptation.

We now turn to some robustness analysis of the results of the structural model. In particular, we consider alternative functional forms.

Table 11 lists the models we consider. Specification (A) is our baseline model, reported in the main text, and copied here for convenience. Specification (B) is the same model, estimated using the identity weighting matrix rather than the inverse-variance weighting matrix used in the paper. Specifications (C) and (D) are the baseline model, except that we change the value of the parameter $\overline{T}$ at which losses start; recall that the function f is given by, for $T_{it} \geq \overline{T}$:

$$\log f(T_{it}, k_i) = b_0 - \overline{b_1} e^{-k/\theta}(T_{it} - \overline{T}). \tag{5}$$

Specifications (E)-(G) assume quadratic, rather than linear, losses, i.e.

$$\log f(T_{it}, k_i) = b_0 - \overline{b_2} e^{-k/\theta}(T_{it} - \overline{T})^2, \tag{6}$$

with different values for $\overline{T}$: 26°C, 24°C, 28°C. Specifications (H) and (I) adjust the risk aversion coefficient to either 0 or 4 (rather than 1 (log utility) in the baseline). Specifications (J)-(P) experiment with the adaptation technology. First, instead of the exponential form, we try an inverse form:

$$\log f(T_{it}, k_i) = b_0 - \frac{\overline{b_1}}{1 + k/\theta}(T_{it} - \overline{T}), \tag{7}$$

or an inverse-squared root:

$$\log f(T_{it}, k_i) = b_0 - \frac{\overline{b_1}}{1 + \sqrt{k/\theta}}(T_{it} - \overline{T}), \tag{8}$$

or inverse-quadratic:

$$\log f(T_{it}, k_i) = b_0 - \frac{\overline{b_1}}{1 + (k/\theta)^2}(T_{it} - \overline{T}). \tag{9}$$

Next, we also try an exponential-quadratic:

$$\log f(T_{it}, k_i) = b_0 - \overline{b_1} e^{-(k/\theta)^2}(T_{it} - \overline{T}), \tag{10}$$

or exponential-squared root:

$$\log f(T_{it}, k_i) = b_0 - \overline{b_1} e^{-\sqrt{k/\theta}}(T_{it} - \overline{T}). \tag{11}$$

Last and more ambitiously, we tried two models with 3-parameters, the curvature ω, either using the inverse formulation:

$$\log f(T_{it}, k_i) = b_0 - \frac{\overline{b_1}}{1 + (k/\theta)^{\omega}}(T_{it} - \overline{T}), \tag{12}$$

or the exponential formulation:

$$\log f(T_{it}, k_i) = b_0 - \overline{b_1} e^{-(k/\theta)^{\omega}} (T_{it} - \overline{T}). \tag{13}$$

Table 12 shows parameter estimates and associated standard errors for each specification. Table 13 shows how each specification fits the targeted moments. And table 14 calculates the losses in the RCP 6.0 scenario for each estimated model.

The main lessons we draw are as follows. First, there is no specification that fits the data much better than our simple baseline model, as measured by the J-stat for instance, except perhaps for specification (M) - the exponential-quadratic specification or (O) - the inverse-power specification (with a power exponent ω close to 5). These specifications do a slightly better job at matching the very small (and fairly precisely measured) sensitivity of the hottest quintile. Some specifications do poorly, such as the inverse, inverse quadratic or inverse square root. Apart from these extremes, the other specifications fit the data about equally well.

Second, the implications of these different models for the median and standard deviation of losses are fairly similar, with some easy-to-understand exceptions. Looking at table 14, losses are higher for the quadratic loss model, and for models with $\overline{T} = 28°C$. This is expected, as the costs of very high temperature are higher with these specifications - directly in the quadratic case, and indirectly in the case of $\overline{T} = 28°C$ because the model then estimates a steeper slope $\overline{b_1}$ to fit the observed sensitivities to temperature. Recall, however, that there is no clear empirical support for the quadratic form or the high $\overline{T}$. More importantly, the main point of the paper - that adaptation makes a meaningful difference to this calculation - remains true even in this case: the median and SD of losses are much lower in the endogenous adaptation case.

Third, changing risk aversion or the weighting matrix makes little difference to our results.

Fourth, the adaptation technology does affect how much the median loss is reduced due to adaptation. For our baseline model, the difference between the median loss with fixed and endogenous adaptation is 1.13 point. Under some technologies with more steeply decreasing returns to adaptation, such as the exponential-quadratic function, or the inverse-power function, the difference is only 0.54 point (resp. 0.55). These functional forms, of course, are also those that fit the data slightly better. One reason to stick with the current functional form is parsimony, but a possible extension is to estimate the model using a wider set of moments to choose the best-fitting adaptation technology.

Source	Code
Baseline	A
Identity Weighting matrix	B
Tbar=24C	C
Tbar=28C	D
Quadratic	E
Quad.:Tbar=24C	F
Quad.:Tbar=28C	G
risk aversion 0	H
risk aversion 4	I
Adapt. cost inverse	J
Adapt. cost inverse-sqrt	K
Adapt. cost inverse-quad	L
Adapt. cost exp-quad	M
Adapt. cost exp-sqrt	N
Adapt. cost inverse-power	O
Adapt. cost exp-power	P

Table 11: This table lists the different specifications of the structural model and provides a reference letter for each model for the other exhibits.

param	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P
$\overline{T}$	26.000	26.000	24.000	28.000	26.000	24.000	28.000	26.000	26.000	26.000	26.000	26.000	26.000	26.000	26.000	26.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
b_1	0.161	0.191	0.099	6.239	.	.	.	0.159	0.164	0.304	0.951	0.096	0.105	0.533	0.108	0.167
	(.007)	(.011)	(.003)	(1.501)	(.)	(.)	(.)	(.006)	(.006)	(.042)	(2.935)	(0.000)	(0.000)	(.07)	(.001)	(.007)
b_2	.	.	.	.	0.058	0.020	2.275	.	.	.	.	.	.	.	.	.
	(.)	(.)	(.)	(.)	(.001)	(0.000)	(.731)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
θ	0.013	0.011	0.019	0.011	0.011	0.014	0.013	0.013	0.013	0.001	0.000	0.011	0.019	0.002	0.020	0.012
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ω	.	.	.	.	.	.	.	.	.	.	.	.	.	.	5.637	0.984
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(4.892)	(.029)

Table 12: Parameter estimates and associated standard errors for the various specifications of the structural model detailed above. A missing standard error (denoted by (.)) implies that a parameter is either a plugged value if the parameter value is not missing or not included in the model if the parameter value is missing.

Source	Quintile1	Quintile2	Quintile3	Quintile4	Quintile5	Jstat	pval
Data	-0.117	-0.091	-0.065	-0.042	-0.008	.	.
SE	0.075	0.048	0.020	0.009	0.009	.	.
A	-0.088	-0.096	-0.072	-0.035	-0.017	1.881	0.598
B	-0.099	-0.109	-0.066	-0.031	-0.015	2.200	0.532
C	-0.097	-0.099	-0.064	-0.036	-0.019	2.125	0.547
D	-0.085	-0.106	-0.068	-0.035	-0.017	1.951	0.583
E	-0.082	-0.097	-0.072	-0.035	-0.017	1.874	0.599
F	-0.090	-0.099	-0.068	-0.035	-0.018	1.875	0.599
G	-0.075	-0.093	-0.062	-0.035	-0.019	2.393	0.495
H	-0.087	-0.096	-0.071	-0.035	-0.017	1.734	0.629
I	-0.089	-0.097	-0.070	-0.036	-0.017	1.688	0.639
J	-0.119	-0.076	-0.049	-0.035	-0.025	4.737	0.192
K	-0.074	-0.055	-0.041	-0.033	-0.028	7.954	0.047
L	-0.057	-0.062	-0.066	-0.039	-0.019	2.455	0.483
M	-0.066	-0.069	-0.072	-0.042	-0.008	0.821	0.663
N	-0.143	-0.095	-0.057	-0.035	-0.021	2.830	0.419
O	-0.062	-0.067	-0.072	-0.042	-0.008	0.908	0.823
P	-0.091	-0.098	-0.071	-0.035	-0.017	1.768	0.413

Table 13: Targeted moments with estimated standard errors together with the model moments at the estimated parameters for the various specifications detailed above.

	Fixed Adaptation		Endogenous Adaptation	
	Median	Std. Dev	Median	Std. Dev
Baseline	-2.93	1.49	-1.80	0.65
Identity Weighting matrix	-2.80	1.55	-1.64	0.62
Tbar=24C	-2.86	1.21	-2.02	0.69
Tbar=28C	-4.64	2.55	-2.83	1.26
Quadratic	-4.14	2.04	-2.20	0.76
Quad.:Tbar=24C	-3.49	1.51	-2.09	0.66
Quad.:Tbar=28C	-5.81	3.17	-4.08	1.48
risk aversion 0	-2.94	1.48	-1.81	0.66
risk aversion 4	-2.95	1.50	-1.81	0.66
Adapt. cost inverse	-2.88	1.06	-2.00	0.55
Adapt. cost inverse-sqrt	-2.65	0.94	-1.98	0.73
Adapt. cost inverse-quad	-2.47	1.37	-1.76	0.63
Adapt. cost exp-quad	-2.15	1.77	-1.61	0.84
Adapt. cost exp-sqrt	-3.09	1.34	-1.90	0.50
Adapt. cost inverse-power	-2.18	1.87	-1.63	0.85
Adapt. cost exp-power	-2.96	1.49	-1.81	0.65

Table 14: Cross-county statistics for different structural models in the RCP 6.0 scenario. (As in Table 2 in the text.)

References

Deryugina, T. and S. M. Hsiang (2014). Does the environment still matter? daily temperature and income in the united states. Technical report, National Bureau of Economic Research.