Appendix Materials for Online Publication: "A Forward-Looking Ricardian Approach: Do Land Markets Capitalize Climate Change Forecasts?"

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Appendix I: Excluded counties and county equivalents

The inverse distance weighting method used to translate gridded climate data from Hadley 3 and CCSM 3 to county centroid data experienced minor issues in some counties at the geographic edge of our sample in Michigan and Florida. Independent cities (which are county equivalents) in Virginia are also excluded; these are typically smaller in land area and urbanized. Weighting failed to produce estimates for one county in Missouri. By state, these counties and county equivalents are:

FLORIDA: Miami-Dade, Monroe.

MICHIGAN: Alcona, Alpena, Charlevoix, Cheboygan, Chippewa, Emmet, Keneenaw, Luce, Mackinac, Montmorency, Ostego, Preqsue, Sanilac, Schoolcraft.

MISSOURI: Ste. Genevieve.

VIRGINIA: Albemarle, Alleghany, August, Bedford, Campbell, Carroll, Dinwiddie, Fairfax, Frederick, Greensville, Henry, Montgomery, Pittsylvania, Prince George, Prince William, Roanoke, Rockbridge, Rockingham, Southampton, Spotsylvania, Washington, Wise.

Appendix II: Alternate models

Climate uncertainty

This section briefly describes a simple way in which climate uncertainty could enter into the model presented in the main body of the paper.

Suppose that the future sequence of states $\mathcal{S}_t$ is uncertain, but that the market anticipates the possibility of change in the state. Market information about the evolution of states at time $t = 0$ is public and denoted by Σ. Belief formation over the evolution of the state space is the process of mapping information to a set of probability spaces. These probability spaces share support Ω (the state space) and an appropriate σ-algebra, but possess potentially different probability measures for each period from $t = 0$ until the market's horizon T periods later.[a] Beliefs about period $t \neq 0$ formed in period $t = 0$ are represented by a probability density function over states: f_t. Thus, market beliefs are the mapping:

$$\Sigma \rightarrow \{f_0, f_1, \ldots, f_T\}$$

The market information set is the product of a series of distributions from the current period into the future; given a set of realizations (one from each period), prices would be deterministic. Market beliefs, in the form of this sequence of distributions, can take any path. For example, if climate change implied local warming with constant variance, then f_{t+1} would stochastically dominate f_t in each period. Under no arbitrage, the market capitalizes this information in an efficient manner and the pricing function can be recast as an expectation that now depends on the information set Σ:

$$P(\Sigma) = \mathbb{E}_0[\sum_{t=0}^{\infty} \delta^t p(\mathcal{S}_t)] = \sum_{t=0}^{\infty} \left(\delta^t \int_{s \in \Omega} p(s) f_t(s) ds \right)$$

Rewriting this in terms of the linear approximation and simplifying gives:

$$P(\Sigma) = aD + b \sum_{t=0}^{\infty} \delta^t \mathbb{E}_0[\mathcal{S}_t] \tag{A1}$$

Under uncertainty about future states, our implicit assumption of risk neutrality implies that the market prices the asset according to the expectation of the evolution of the state. Thus, only the path of mean beliefs determine prices.

The use of risk neutrality here is neither necessary nor as strong an assumption as it may seem. While individual farmers may be risk averse, the presence of crop insurance means that

a. In principle, T could be ∞. In practice, we restrict T to be about 100 years. For reasonable values of δ, the role of periods beyond 100 years in the future is minimal.

they are somewhat protected from annual fluctuations in weather, mitigating the effects of risk. Further, we use spatially delineated fixed effects to control for the potentially correlated effects of variability, to which uncertainty could contribute; see below.

Under the assumptions of this simple model, the path of mean forecasted states $\{\mathbb{E}_0[\mathcal{S}_t]\}_{t=0}^{\infty}$ and knowledge of the slope of the rental function p with respect to the state are sufficient to describe prices. Further, if the asset rental rate equation is quadratic in the state variable (as modeled in MNS and virtually all other applications of the Ricardian method), a variant of this sufficiency holds with one additional assumption: If $Var(\mathcal{S}_t)$ is constant (or exogenous) across observations, then again only the mean belief path matters. However, if places with systematically higher draws of $\mathcal{S}_t$ also experience systematically higher or lower variance than $\mathcal{S}_t$, then Equation (A1) should be augmented to include a variance and covariance terms, as in Kelly et al. (2005). For example, consider the quadratic case, $P = \sum_{t=0}^{\infty} \delta^t (a + b_0\mathbb{E}[\mathcal{S}_t] + b_1\mathbb{E}[\mathcal{S}_t^2])$, which can be expressed as $P = \sum_{t=0}^{\infty} \delta^t (a + b_0\mathbb{E}[\mathcal{S}_t] + b_1(Var[\mathcal{S}_t] + \mathbb{E}[\mathcal{S}_t]^2))$. We include the squared expectation term in our specifications. Thus only the variance term is troubling; the variance term can be interpreted as capturing a local approximation of risk. Its presence only adversely impacts empirics only if the variance of beliefs about climate in each year varies across location in a way that is systematically correlated with expected climate. Instead, we include spatially delineated fixed effects in our empirical analysis to limit the impacts of this variance term.

Again consider two different scenarios, one describing a world with a constant state ($\mathcal{S}_t = \mathcal{S}_0 \ \forall t$) and the other where a distribution of potential state changes is anticipated. Assume that $\delta < 1$ and $|\lim_{t\to\infty} \mathbb{E}[\mathcal{S}_t]| < \infty$. Let the climate change be:

$$I \equiv \sum_{t=0}^{\infty} \mathcal{S}_0 \delta^t \quad \text{(i.e., the \textit{No Change} index)} \tag{A2}$$

$$Y \equiv \sum_{t=0}^{\infty} \mathbb{E}_0[\mathcal{S}_t] \delta^t \quad \text{(i.e., the \textit{Mean Forecast} index)} \tag{A3}$$

To illustrate the consequences, we derive the correlation between $\mathcal{S}_{0i}$ and Y_i. This requires assuming a model describing how expectations about the future state are formed so that we can derive a practical expression for Y that can be implemented with available data. For simplicity, consider the case where beliefs have discrete support, assigning probabilities with positive measure to a finite number of (potentially time-varying) values in the state space.[b] Equation (A1) can be partitioned into a component that depends on the current state ($\mathcal{S}_{0i}$), and a component derived from alternative expectations about $\mathcal{S}_{ti}$. Define by $\pi_t = \Pr(\mathcal{S}_{ti} = \mathcal{S}_{0i})$ the probability that the current state is realized in period t. Then:

$$Y_i = \left(\sum_{t=0}^{\infty} \delta^t \pi_t\right) \mathcal{S}_{0i} + \left(\sum_{t=0}^{\infty} \delta^t (1 - \pi_t) \mathbb{E}[\mathcal{S}_{ti} | \mathcal{S}_{ti} \neq \mathcal{S}_{0i}]\right)$$

b. In the climate change example, this would be like assigning a (potentially time-varying) probability to each path of climate change available in the IPCC reports.

and so

$$P_i(Y_i) \;=\; \alpha + b\left(\sum_{t=0}^{\infty}\delta^t\pi_t\right)\mathcal{S}_{0i} + b\left(\sum_{t=0}^{\infty}\delta^t(1-\pi_t)\mathbb{E}[\mathcal{S}_{ti}|\mathcal{S}_{ti}\neq\mathcal{S}_{0i}]\right) + \varepsilon_i^Y \tag{A4}$$

If the analyst proceeds following the standard Ricardian approach (omitting the second term in parentheses in the equation above), the bias in the regression estimate of β is given by:

$$\begin{aligned}\hat{\beta} \xrightarrow{p} & \frac{Cov(\mathcal{S}_{0i}, b\left(\sum_{t=0}^{\infty}\delta^t\pi_t\right)\mathcal{S}_{0i} + b\left(\sum_{t=0}^{\infty}\delta^t(1-\pi_t)\mathbb{E}[\mathcal{S}_{ti}|\mathcal{S}_{ti}\neq\mathcal{S}_{0i}]\right))}{V(\mathcal{S}_{0i})} \\ &= b\sum_{t=0}^{\infty}\delta^t\left(\pi_t + (1-\pi_t)Corr(\mathcal{S}_0, \mathbb{E}[\mathcal{S}_t|\mathcal{S}_t\neq\mathcal{S}_0])\sqrt{\frac{V(\mathbb{E}[\mathcal{S}_t|\mathcal{S}_t\neq\mathcal{S}_0])}{V(\mathcal{S}_0)}}\right)\end{aligned} \tag{A5}$$

This reveals that the parameter estimate $\hat{\beta}$ depends on the true parameter b as well as the magnitude of and confidence in alternative forecasts.

Result 1. *The standard Ricardian approach gives a consistent estimate of* β *(*$\widehat{\beta} \xrightarrow{p} \beta$*) only if one or both of the following are true: (1) The market places no probability on the possibility of change (*$1-\pi_t = 0$*) for all* t*, or (2) the product of the correlation term and ratio of standard deviations in Equation (22) precisely equals one. Note that in that case* $\widehat{\beta} \xrightarrow{p} \beta \equiv bD$*.*

Both of these conditions seem unlikely in most applications, even in scenarios that intuition from standard OLS indicates should not cause concern. For example, (i) even if the omitted variable (representing mean alternative beliefs) is orthogonal to the observed (historical) covariate, there could still be bias. There could still be bias (ii) even if there is no variation in the expected state across space. In both cases, estimates are attenuated.[c] Just as with Result 1, there is one important case in which bias does not arise: If beliefs are the current state plus an additive term that is constant across observations in each period.[d]

Bias under piecewise linear regression

As in the Section 3.1, assume that the *Mean Forecast* is a weighted sum of the *No Change* index and the *Observed Forecast*:

$$Y = \omega I + (1-\omega)F \tag{A6}$$

c. If (i) were true, $Corr(\mathcal{S}_0, \mathbb{E}[\mathcal{S}_t|\mathcal{S}_t \neq \mathcal{S}_0]) = 0$. If (ii) were true, then $V(\mathcal{S}_t) = 0$. In either case, $\hat{\beta} \xrightarrow{p} b\sum_{t=0}^{\infty}\delta^t\pi_t \leq bD$.

d. In this case, $V(\mathbb{E}[\mathcal{S}_t|\mathcal{S}_t \neq \mathcal{S}_0]) = V(\mathcal{S}_0)$ and $Corr(\mathcal{S}_0, \mathbb{E}[\mathcal{S}_t|\mathcal{S}_t \neq \mathcal{S}_0]) = 1$ in each period, so $\hat{\beta} \xrightarrow{p} b\sum_{t=0}^{\infty}\delta^t(\pi_t + (1-\pi_t)) = bD$ and there is no bias.

Suppose the true model of prices follows a two-segment piecewise linear form in Y:

$$P = P(Y) = b_1 Y + b_2 Y D_{Y>0} + \epsilon \tag{A7}$$

where the equation is demeaned and the breakpoint in the linear function has been normalized to zero (this is without loss of generality and facilitates exposition). $D_{Y>0}$ is an indicator equal to one if $Y > 0$ and zero else, and ϵ is uncorrelated with both I and F, and thus Y.

The naive econometrician does not account for market anticipation, and instead estimates a two-segment piecewise linear regression model using the same breakpoint, but the wrong information:

$$P = b_1^I I + b_2^I I D_{I>0} + u \tag{A8}$$

Denote the estimates from OLS estimation of this equation as $\tilde{b}_1^I$ and $\tilde{b}_2^I$.

To simplify statements about bias, it helps to reframe the problem as one of separate estimation on several subsets of the data. This breaks the nonlinearity in the forecast that is implicit in the PLR model, and recasts it as several linear estimation problems. It will be useful to consider first two derivations:

Lemma 1. *Divide observations into the following sets:*

$$\begin{aligned} S_1 &= \{(Y, I) : Y \leq 0, I \leq 0\} \\ S_2 &= \{(Y, I) : Y > 0, I \leq 0\} \\ S_3 &= \{(Y, I) : Y \leq 0, I > 0\} \\ S_4 &= \{(Y, I) : Y > 0, I > 0\} \end{aligned}$$

Denote the estimated coefficients from running the regression model in equation (3) separately on each set of data S_k as $\tilde{g}_k$ for $k = 1, 2, 3, 4$. Then $\tilde{b}_1 = \tilde{v}_1 \tilde{g}_1 + (1 - \tilde{v}_1)\tilde{g}_2$ and $\tilde{b}_2 = \tilde{v}_3 \tilde{g}_3 + (1 - \tilde{v}_3)\tilde{g}_4 - \tilde{b}_1$, with $\tilde{v}_1 = \frac{\sum_{i \in S_1} I_i^2}{\sum_{i \in (S_1 \cup S_2)} I_i^2}$ and $\tilde{v}_3 = \frac{\sum_{i \in S_3} I_i^2}{\sum_{i \in (S_3 \cup S_4)} I_i^2}$

Proof of Lemma 1. First, note that $\tilde{g}_k = \frac{\sum_{i \in S_k} I_i P_i}{\sum_{i \in S_k} I_i^2}, k = 1, 2, 3, 4$. Next, note that

$$\begin{aligned} \tilde{b}_1 &= \frac{\sum_{\forall i} I_i P_i - \sum_{\forall i} I_i D_{I_i>0} P_i}{\sum_{\forall i} I_i^2 - \sum_{\forall i} I_i^2 D_{I_i>0}} \\ &= \frac{\sum_{i \in (S_1 \cup S_2)} I_i P_i}{\sum_{i \in (S_1 \cup S_2)} I_i^2} \end{aligned}$$

and

$$\tilde{b}_2 = \frac{\sum_{\forall i} I_i^2 \cdot \sum_{\forall i} I_i D_{I_i>0} P_i - \sum_{\forall i} I_i^2 D_{I_i>0} \cdot \sum_{\forall i} I_i P_i}{\sum_{\forall i} I_i^2 D_{I_i>0} \cdot (\sum_{\forall i} I_i^2 - \sum_{\forall i} I_i^2 D_{I_i>0})}$$

$$= \frac{\sum_{i\in(S_1\cup S_2)} I_i^2 \cdot \sum_{i\in(S_3\cup S_4)} I_i P_i - \sum_{i\in(S_3\cup S_4)} I_i^2 \cdot \sum_{i\in(S_1\cup S_2)} I_i P_i}{\sum_{i\in(S_1\cup S_2)} I_i^2 \cdot \sum_{i\in(S_3\cup S_4)} I_i^2}$$

It then follows directly that $\tilde{b}_1 = \tilde{v}_1\tilde{g}_1 + (1-\tilde{v}_1)\tilde{g}_2$ and $\tilde{b}_2 = \tilde{v}_3\tilde{g}_3 + (1-\tilde{v}_3)\tilde{g}_4 - \tilde{b}_1$. □

Lemma 1 essentially shows that for the PLR model, the coefficients that results from estimating equation (3) are just the variance weighted averages of the coefficients resulting from running separate regressions on the conditioning set.

Lemma 2. *Denote $\rho_{I,F|S_k} = \mathbb{E}[I_i F_i|S_k]$ and $\sigma^2_{I|S_k} = \mathbb{E}[I_i^2|S_k]$. If $S_k \neq \varnothing$ and standard regularity conditions hold, then the separately estimated regressions coefficients $\tilde{g}_k$ converge as follow:*

$$\tilde{g}_1 \to_p b_1 \left(\omega + (1-\omega)\frac{\rho_{I,F|S_1}}{\sigma^2_{I|S_1}}\right)$$

$$\tilde{g}_2 \to_p (b_1 + b_2) \left(\omega + (1-\omega)\frac{\rho_{I,F|S_2}}{\sigma^2_{I|S_2}}\right)$$

$$\tilde{g}_3 \to_p b_1 \left(\omega + (1-\omega)\frac{\rho_{I,F|S_3}}{\sigma^2_{I|S_3}}\right)$$

$$\tilde{g}_4 \to_p (b_1 + b_2) \left(\omega + (1-\omega)\frac{\rho_{I,F|S_4}}{\sigma^2_{I|S_4}}\right)$$

Proof of Lemma 2. Follows directly from the definitions given and Slutsky's theorems. □

Lemma 2 simply states that, if the estimates from the individual regressions on sets S_k are available, they converge in probability to the limiting values given above. These useful statements can be combined to show that the OLS estimates from equation (3) converge in value to the following (assuming that no S_k are empty):

$$\tilde{b}_1 \to_p b_1 \cdot \frac{\sigma^2_{I|S_1}}{\sigma^2_{I|S_1} + \sigma^2_{I|S_2}} \left(\omega + (1-\omega) \frac{\rho_{I,F|S_1}}{\sigma^2_{I|S_1}} \right) + (b_1 + b_2) \cdot \frac{\sigma^2_{I|S_2}}{\sigma^2_{I|S_1} + \sigma^2_{I|S_2}} \left(\omega + (1-\omega) \frac{\rho_{I,F|S_2}}{\sigma^2_{I|S_2}} \right)$$

$$\tilde{b}_1 + \tilde{b}_2 \to_p b_1 \cdot \frac{\sigma^2_{I|S_3}}{\sigma^2_{I|S_3} + \sigma^2_{I|S_4}} \left(\omega + (1-\omega) \frac{\rho_{I,F|S_3}}{\sigma^2_{I|S_3}} \right) + (b_1 + b_2) \cdot \frac{\sigma^2_{I|S_4}}{\sigma^2_{I|S_3} + \sigma^2_{I|S_4}} \left(\omega + (1-\omega) \frac{\rho_{I,F|S_4}}{\sigma^2_{I|S_4}} \right)$$

Before proceding, it is useful to clarify a particular feature of misinformation using the PLR model: observations can potentially be misclassified if they are moved across the breakpoint. This can be expressed by set membership:

Definition 1. *Misclassification occurs if $S_2 \cup S_3 \neq \varnothing$. No misclassification means $S_2 = S_3 = \varnothing$.*

Now, the primary result:

Theorem 1. *Under the PLR model with $b_1 \neq b_2 \neq 0$, if market beliefs are a mixture of the* No Change *index and the* Observed Forecast *index, the standard Ricardian approach gives consistent estimates of b_1 and b_2 ($\tilde{b}_1 \xrightarrow{p} b_1$ and $\tilde{b}_2 \xrightarrow{p} b_2$) if either*

the No Change *index never misclassifies an observation, and $\omega = 1$; or*

the No Change *index never misclassifies an observation, and $\frac{\rho_{I,F|S_k}}{\sigma^2_{I|S_k}} = 1$ for $k = 1, 4$.*

Proof of Theorem 1. Under no misclassification, estimates of $\tilde{g}_2$ and $\tilde{g}_3$ are unavailable, and the misspecified estimates of Equation (3) converge to:

First, no misclassification is necessary condition. Suppose that there is misclassification. Then $S_2 \cup S_3 \neq \varnothing$ and at least one of $\tilde{g}_2$ and $\tilde{g}_3$ exists. So one of the three scenarios holds and follows from Lemmas 1 and 2: (i) if $S_2 = \varnothing$ and $S_3 \neq \varnothing$:

$$\tilde{b}_1 \to_p b_1 \cdot \left(\omega + (1-\omega) \frac{\rho_{I,F|S_1}}{\sigma^2_{I|S_1}} \right)$$

$$\tilde{b}_1 + \tilde{b}_2 \to_p (b_1 + b_2) \cdot \left(\omega + (1-\omega) \frac{\rho_{I,F|S_4}}{\sigma^2_{I|S_4}} \right)$$

If $\omega = 1$, then $\tilde{b}_j \rightarrow_p b_j$. Likewise, if all $\frac{\rho_{I,F|S_k}}{\sigma^2_{I|S_k}} = 1$ for $k = 1, 4$, then $\tilde{b}_j \rightarrow_p b_j$ $\square$

Appendix Table 1: Summary Statistics on Farmland Values and Historical Climate Variables

	Mean	Std Dev	Minimum	Maximum
1. Average Farmland Value Per Acre	2,833.7	1,517.7	449.4	20,173.7
2. Historical Climate Variables				
Growing Season Mean Temperature	69.1	5.6	55.6	82.9
Winter Temperature	34.9	11.0	7.4	65.4
Spring Temperature	55.2	7.7	38.3	75.0
Summer Temperature	75.1	4.8	63.1	86.3
Fall Temperature	57.2	7.2	39.9	76.8
Winter Precipitation	2.8	1.4	0.4	5.7
Spring Precipitation	3.8	0.9	1.4	5.7
Summer Precipitation	4.1	0.8	2.1	8.2
Fall Precipitation	3.4	0.8	1.2	6.0
3. Discounted Historical Climate Indices				
Growing Season Mean Temperature	2,221.7	178.7	1,785.4	2,663.5
Winter Temperature	1,120.1	352.9	239.4	2,100.2
Spring Temperature	1,775.4	246.4	1,230.5	2,410.1
Summer Temperature	2,412.8	153.4	2,026.2	2,773.2
Fall Temperature	1,839.0	230.4	1,281.1	2,468.2
Winter Precipitation	91.1	46.4	13.5	183.4
Spring Precipitation	122.6	28.3	44.8	183.9
Summer Precipitation	131.2	24.4	66.9	264.9
Fall Precipitation	109.2	25.5	38.0	193.8

Notes: Sample means and standard deviations for 2,112 counties in main estimation sample (counties east of 100th meridian) in 2007. Discounted indices based on 3% discount rate. See the text for more details.

Appendix Table 2: Estimated Coefficients and Predicted Climate Change Impacts from Forward-Looking Ricardian Regressions in Quadratic Seasonal Climate Indices, 2007 Cross-Section

	Beliefs based on CCSM 3 A2				Beliefs based on Hadley 3 A2			
Parameter	(1a)	(1b)	(1c)	(1d)	(2a)	(2b)	(2c)	(2d)
ω	0.50***	(0.15)	0.51*	(0.19)	0.33*	(0.13)	0.31**	(0.11)
Linear winter temperature index	-16.53	(11.40)	-10.98	(9.69)	-26.12*	(9.93)	-13.87	(9.88)
Linear spring temperature index	32.50	(34.24)	-23.04	(20.39)	53.65	(36.18)	-11.62	(20.67)
Linear summer temperature index	63.75	(56.94)	58.02	(51.19)	-2.70	(50.14)	17.85	(48.56)
Linear fall temperature index	40.86	(56.05)	66.73	(44.86)	80.52	(63.86)	79.99+	(45.97)
Linear winter precipitation index	-63.75+	(33.55)	-71.82*	(35.25)	-105.11	(65.47)	-127.14*	(48.63)
Linear spring precipitation index	76.26*	(29.29)	49.55	(30.26)	58.35*	(26.13)	39.50	(29.80)
Linear summer precipitation index	-120.88***	(28.90)	-69.53***	(19.04)	-111.58**	(39.39)	-55.55**	(18.78)
Linear fall precipitation index	119.28**	(40.94)	86.17*	(37.74)	178.32*	(85.28)	140.08*	(56.32)
Quad winter temperature index	0.24	(0.17)	0.16	(0.14)	0.38*	(0.16)	0.23	(0.14)
Quad spring temperature index	-0.28	(0.29)	0.21	(0.17)	-0.49	(0.30)	0.07	(0.17)
Quad summer temperature index	-0.50	(0.34)	-0.43	(0.32)	-0.07	(0.30)	-0.15	(0.30)
Quad fall temperature index	-0.31	(0.49)	-0.57	(0.39)	-0.61	(0.55)	-0.67+	(0.37)
Quad winter precipitation index	11.97*	(5.51)	11.37*	(5.57)	17.85	(0.16)	18.75*	(7.18)
Quad spring precipitation index	-9.83**	(3.42)	-5.06	(3.37)	-7.33*	(0.30)	-3.31	(3.02)
Quad summer precipitation index	11.64***	(3.33)	6.70***	(1.94)	9.96*	(0.30)	4.88*	(1.80)
Quad fall precipitation index	-14.15*	(6.18)	-10.33+	(5.15)	-23.27+	(0.55)	-18.43*	(8.35)
F-statistic on 16 indices	14.04		13.31		15.72		9.96	
[p-value]	[0.000]		[0.000]		[0.000]		[0.000]	
Present Value of Climate Change Impacts								
CCSM 3	---	---	-395.7+	(215.3)			-707.5*	(274.7)
Hadley 3			-403.7+	(249.6)			-776.5*	(333.6)
State Fixed Effects	No		Yes		No		Yes	

Appendix Table 3: Estimated Coefficients and Predicted Climate Change Impacts from Forward-Looking Ricardian Regressions in Binned Climate Indices, 2007 Cross-Section

	Beliefs based on CCSM 3 A2				Beliefs based on Hadley 3 A2			
Parameter	(1a)	(1b)	(1c)	(1d)	(2a)	(2b)	(2c)	(2d)
ω	0.05	(0.21)	0.37**	(0.12)	-0.06	(0.14)	0.25**	(0.09)
Daily Average Temperature Index:								
Number of Days Less Than 10 °F	1.27	(0.81)	-0.56	(0.73)	1.06	(0.70)	-0.10	(0.84)
Number of Days Between 10-19 °F	0.99+	(0.49)	0.95+	(0.54)	0.88*	(0.41)	0.33	(0.47)
Number of Days Between 20-29 °F	1.29*	(0.57)	0.07	(0.48)	0.90	(0.63)	-0.12	(0.48)
Number of Days Between 30-39 °F	0.83*	(0.33)	0.40	(0.38)	0.41	(0.27)	0.25	(0.40)
Number of Days Between 40-49 °F	0.64*	(0.25)	-0.11	(0.26)	0.77*	(0.34)	-0.07	(0.30)
Number of Days Between 50-59 °F	---	---	---	---	---	---	---	---
Number of Days Between 60-69 °F	0.15	(0.58)	0.00	(0.59)	0.26	(0.45)	0.19	(0.56)
Number of Days Between 70-79 °F	0.83*	(0.35)	0.67*	(0.27)	0.97**	(0.29)	0.72*	(0.31)
Number of Days Between 80-89 °F	-0.69+	(0.36)	-0.82*	(0.39)	-0.69*	(0.34)	-0.93*	(0.36)
Number of Days Greater Than 90 °F	-0.13	(0.54)	0.06	(0.61)	-0.49	(0.32)	-0.11	(0.50)
Annual Precipitation Index:								
Annual Precipitation Less Than 24 in	-51.28***	(12.96)	-40.05**	(11.55)	-65.49***	(17.27)	-39.19**	(14.44)
Annual Precipitation Between 24-36 in	-10.02	(11.62)	-9.42	(8.73)	-3.54	(20.48)	-1.93	(9.51)
Annual Precipitation Between 36-43 in	---	---	---	---	---	---	---	---
Annual Precipitation Between 43-51 in	-2.66	(13.28)	-10.82	(8.83)	-24.27	(22.11)	-16.74	(12.48)
Annual Precipitation Greater Than 51 in	9.24	(10.73)	21.52*	(10.40)	1.66	(16.16)	23.71*	(11.46)
F-statistic on 13 indices	10.43		11.56		11.03		5.24	
[p-value]	[0.000]		[0.000]		[0.000]		[0.000]	
Present Value of Climate Change Impacts								
CCSM 3	---	---	-96.4	(103.9)	---	---	-98.4	(125.8)
Hadley 3	---	---	-65.1	(66.2)	---	---	-88.4	(78.9)
State Fixed Effects	No	No	Yes	Yes	No	No	Yes	Yes