EXTREME WEATHER, EXPERIENTIAL LEARNING, AND SPATIAL SPILLOVERS IN THE CLIMATE OPINION FORMATION PROCESS

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ABSTRACT. Climate change is an urgent global challenge, yet public opinion on the issue remains highly polarized and poses challenges to achieving the broad public support needed for effective climate action. While the literature has established relationships between climate opinion and factors such as education, partisanship, and local industry, there is less consensus on the role of experiential cues – especially extreme weather. Methodological challenges, including the failure to account for spatial dependence, have limited our understanding of how extreme weather shapes climate opinion. To address this gap, we apply spatial econometric techniques to evaluate both the direct and indirect effects of extreme weather on climate change beliefs and risk perceptions. We find that extreme weather events exert a significant direct effect on beliefs and risk perceptions, with the former also exhibiting measurable spatial spillovers. Additionally, extreme weather has a stronger direct effect on beliefs than long-term temperature changes. However, spatial spillovers are absent in the formation of risk perceptions, underscoring the importance of personal experience in driving individual safety concerns. Our findings highlight the nuanced mechanisms by which experiential cues shape climate opinion and the importance of accounting for spatial dependence in empirical studies. These insights have practical implications for climate communication and disaster preparedness, particularly as climate change shifts the spatial distribution of extreme weather events across the United States.

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1. Introduction

Scientific evidence regarding climate change is clearer than ever: The earth's climate is changing, these changes are attributable to human activity, and urgent action is required to prevent catastrophic damages in the future (Intergovernmental Panel On Climate Change (IPCC) (2023)). And yet, in stark contrast to the scientific consensus, climate change remains a divisive topic both within and across political boundaries. This is particularly true within the United States, with public opinion estimates from the Yale Program for Climate Communications (Howe et al. (2015)) revealing sharp divides amongst Americans. While there is near universal agreement that climate change is happening in some US counties (for example, 86.7% of adult residents in San Francisco County, California are estimated to believe that global warming is occurring), skepticism is relatively common in many others (for example, at least one-in-three adults are estimated to *not* believe in global warming in 64.8% of US counties). Meanwhile, risk perceptions are similarly variable, with the percentage of the adult population estimated to believe that climate change will harm them personally ranging from as low as 31.4% in Pleasants County, West Virginia to as high as 63.4% in Bronx County, New York.

These observations pose a major challenge to the environmental ambitions of the United States, including its commitment under the Biden administration to achieve net-zero greenhouse gas emissions by 2050 (US Department of State (2021)). Social movements have been central to societal change throughout human history, including environmental activism which has been effective in catalyzing climate action by individuals (Ballew et al. (2024)), firms (Haslam and Godfrid (2023), Lenox and Eesley (2009)), and governments (Olzak and Soule (2009)). However, such movements require sufficiently broad, active, and persistent public support (Snow et al. (2008)) – factors that the Yale Program for Climate Communications' public opinion estimates reveal are unevenly distributed across US counties.

In this paper, we study the role of extreme weather in shaping public perceptions of climate change – inclusive of both beliefs and risk perceptions – at the US county level. This mechanism is firmly grounded in theories of learning and attitude formation. According to Kolb's experiential learning theory (Kolb (1984)), individuals form, test, and refine their judgements based on concrete experiences and observations. By placing an individual's interactions with their external environment at the heart of the learning process, it thus suggests that weather – a tangible, daily phenomenon that everyone is exposed to – provides a signal that may inform individuals' attitudes toward climate change.

Meanwhile, dual process theories (Kahneman (2013)) draw a distinction between two modes of information processing: heuristic (or type 1) processing is fast and instinctive, while systematic (or type 2) processing is slow and deliberative. According to the heuristic-systematic model of attitude formation (Chaiken (1980), Chaiken and Stangor (1987), Chaiken and Ledgerwood (2012)), individuals are effort minimizers and face cognitive constraints in their ability to engage in systematic processing, both of which position heuristic processing as the default mode of information processing. Because climate change often takes a backseat to more immediate daily concerns and engaging with scientific evidence is cognitively challenging (Marx et al. (2007), Weber and Stern (2011)), informational cues that are suitable for heuristic processing may therefore play an outsized role in shaping climate opinion. It thus follows that extreme weather events – which are vivid, emotionally salient, and conceptually aligned with climate change – are not only a feasible mechanism for shaping climate opinion, but perhaps also a particularly likely one.

We are not the first to study this phenomenon, but the presence and characteristics of these effects continue to be debated after more than a decade of research. On the one hand, several studies have found evidence that greater exposure to extreme weather increases climate change beliefs and risk perceptions (Konisky et al. (2016), Hughes et al. (2020), Sloggy et al. (2021)). However, many others fail to identify statistically significant relationships between extreme weather and climate opinion (Brulle et al. (2012), Cutler (2016), Carmichael and Brulle (2017), Lyons et al. (2018)). In light of the strong theoretical basis for experiential learning effects in this setting, these conflicting results are somewhat surprising.

As pointed out by Howe et al. (2019)), one potential explanation for these conflicting results is that previous studies have failed to account for spatial dependence in the climate opinion formation process. Spatial dependence may arise in this setting for a variety of reasons, including social learning between socially connected counties (Bandura (1977), Moussaïd et al. (2013), Bailey et al. (2018)) and exposure to out-of-county informational cues through the news media (Ardia et al. (2020)) or due to migration (Ambinakudige and Parisi (2017)). Crucially, ordinary least squares is ill-suited to evaluating empirical relationships in which a spatially lagged dependent variable is present in the true data generating process, typically[1] resulting in simultaneity bias when the spatially lagged term is included (Anselin (2022)) and omitted variable bias when it is excluded (Anselin and Bera (1998)). However, despite these challenges, previous studies of extreme weather and climate opinion have chosen to adopt ordinary least squares and omit spatially lagged terms without conducting specification tests that could rule out spatial dependence.

This paper addresses this methodological gap by adopting techniques from the spatial econometrics literature (Paelinck and Klaassen (1979), Anselin (1988), LeSage and Pace (2009)), including approaches for modeling the relationship between observational units, testing for spatial dependence, specifying spatial effects in econometric models, and interpreting coefficient estimates in such models. The utility of this approach is twofold. First,

[1]With the exception of spatial weight structures in which each observational unit is treated as a neighbour of every other observational unit (see Lee (2002)), simultaneity bias arises in this setting due to non-zero covariance between the spatially lagged dependent variable and the error term.

it allows us to recover unbiased coefficient estimates that describe the direct, experiential learning effect of extreme weather on climate opinion *even if* spatial dependence is observed. Second, it allows us to also estimate the indirect effect that extreme weather in one county exerts on climate opinion in other counties. These indirect effects are often referred to as *spatial spillovers* and are of significant interest in a wide variety of settings. By adopting these techniques, this paper mirrors the contribution of Kaufmann et al. (2017) to the literature on local warming and climate opinion.

Our results help settle this more than decade-long debate while also revealing important nuances in the climate opinion formation process that were not addressed by previous studies. First, they show that residents of US counties that experience more severe extreme weather are more likely to believe that climate change is happening. We refer to this as the direct experiential learning effect of extreme weather on climate change beliefs. Second, by also incorporating the temperature heuristics proposed by Kaufmann et al. (2017) into our econometric specifications, we find that the direct experiential learning effect of extreme weather on climate change beliefs is two to three times larger than that of longer-term changes in temperature. Third, extreme weather distinguishes itself from temperature-based experiential cues in our results by also producing a direct experiential learning effect on risk perceptions. And fourth, our results demonstrate that spatial spillovers arise in the formation of climate change beliefs, but not risk perceptions.

These findings have important implications for climate communications and disaster preparedness efforts in the United States. While improving public awareness of extreme weather events in other parts of the country is enough to increase climate change beliefs, it takes personal experience to elicit a risk response. Gaining public support for proactive disaster preparedness measures may therefore be challenging in communities that have historically experienced low levels of extreme weather. This is a major practical concern as changes in the spatial distribution of extreme weather in the United States (Peterson et al. (2013), Seager et al. (2015), Trenary et al. (2016), Huang et al. (2018)) mean that many of these communities are increasingly at risk. Climate communicators must therefore find alternative avenues for increasing public awareness of future disaster risks, particularly in emergent high risk areas.

This paper proceeds as follows. In Section 2, we summarize our data. We then outline our empirical strategy in Section 3 and discuss the results of our econometric specifications in Section 4. Concluding remarks are offered in Section 5. Supplementary material is included in the appendices, including a more in-depth discussion of the broader literature on climate opinion through the lens of relevant psychological theories (Appendix A) and additional technical materials (Appendix B).

2. Data

2.1. **Climate Opinion Data.** We obtain data on US county-level climate opinion in 2021 from the Yale Program for Climate Communications (YPCC) (Howe et al. (2015)). In their US Climate Opinion Maps (USCOM), they provide the first and only spatially resolved estimates of climate change beliefs, risk perceptions, and policy preferences in the United States. In this study, we focus our attention on estimates in the former two categories. First, we consider county-level climate change beliefs, where $\%Belief_c$ is the estimated percentage of the adult population in county c that answers "yes" to the question "do you think that global warming is happening?" And second, we consider county-level climate change risk perceptions, where $\%Risk_c$ is the estimated percentage of the adult population in county c that answers "a moderate amount" or "a great deal" to the question "how much do you think global warming will harm you personally?"

Summary statistics for $\%Belief_c$ and $\%Risk_c$ are illustrative of the divisive nature of climate opinion within the United States (see Table 1). Comparisons of $\%Belief_c$ and $\%Risk_c$ across counties reveal sharp geographic divides in climate opinion. While less than half of the adult population believes in climate change in some counties (e.g., $\%Belief_c = 45.287\%$ in Lawrence County, Kentucky), there is a strong consensus in many others (e.g., $\%Belief_c = 86.748\%$ in San Francisco County, California). County-level climate risk perceptions are similarly variable, ranging from as low as 31.397% to as high as 63.372%. These estimates also highlight significant within-county divisions, with climate change beliefs and risk perceptions hanging in the balance in many counties. For example, half of US counties have $\%Belief_c$ values between 45.287% and 64.512% and half have $\%Risk_c$ values between 39.974% and 63.372%.

Table 1. Summary Statistics

Statistic	n	Mean	Median	St. Dev.	Min	Max
$\%Belief_c$	3,108	65.199	64.512	6.156	45.287	86.748
$\%Risk_c$	3,108	41.175	39.974	5.071	31.397	63.372
$HealthImpact_{30,c}$	3,108	0.300	0.107	1.169	0.000	38.166
$AssetImpact_{30,c}$	3,108	9.401	1.546	52.088	0.000	1,280.175
$TMax_c$	3,108	202.165	205.053	29.828	95.774	298.010
$High2016_c$	3,108	23.195	20.935	12.086	0.000	126.710
$Low2016_c$	3,108	10.371	8.994	6.768	0.000	98.376
$\%Bachelor_c$	3,108	23.006	20.500	9.931	0.000	78.700
$\%OilGasMining_c$	3,108	1.042	0.017	3.162	0.000	42.545

Further inspection also reveals that climate opinion in the United States is spatially clustered, reflective of broader regional divides in both beliefs and risk perceptions. Clusters of high and low values are clearly observed in choropleth maps of both $\%Belief_c$ and $\%Risk_c$

(see Figures 1 and 2, respectively), with high levels of belief and risk perceptions tending to occur in urban and coastal regions and low levels tending to occur in parts of the Midwest and Southeast. These visual patterns are further supported by Moran's I test statistics (Moran (1948)) (see Table 2), which confirm significant positive spatial autocorrelation for both variables. This observation is robust to spatial weight specifications based on both social ($\mathbf{W}_{S,10}$) and geographic distance ($\mathbf{W}_{G,10}$)[2].

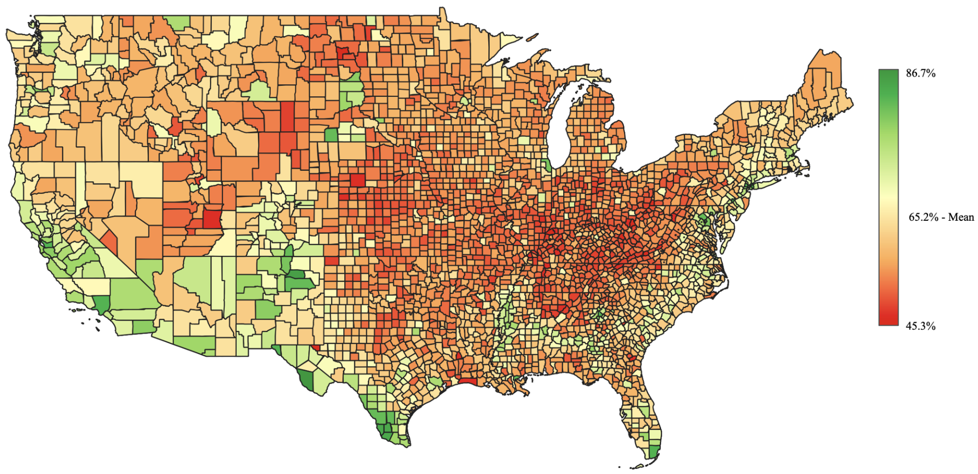

Figure 1. County-level variation in $\%Belief_c$, the percentage of the adult population in county c that believes that global warming is happening.

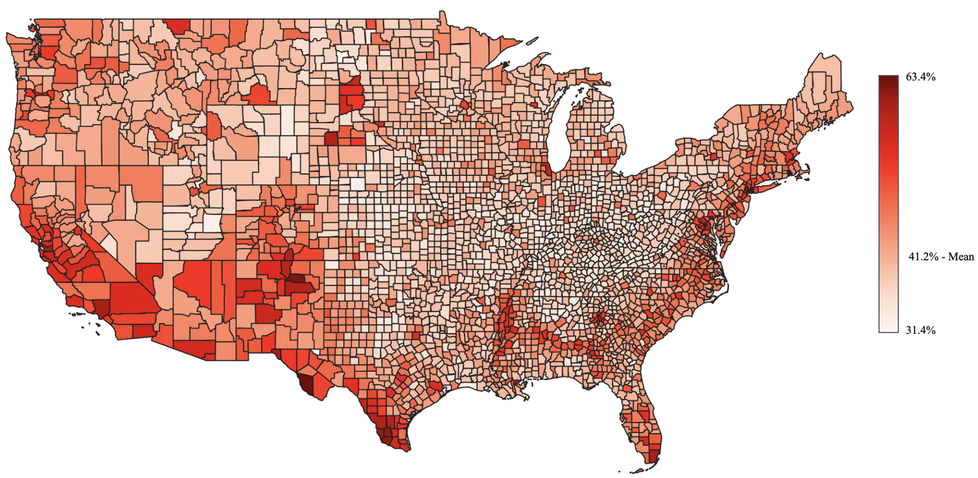

Figure 2. County-level variation in $\%Risk_c$, the percentage of the adult population in county c that believes that global warming will harm them personally.

Finally, as these are survey-based estimates (see Appendix B.1), we note that researchers are limited with respect to the hypotheses they can meaningfully explore using this data. For instance, consider the inclusion of socioeconomic variables such as educational attainment

[2]see Section 2.5 for more information on the spatial weight specifications utilized in this paper.

Table 2. Global Moran's I test statistic and variance under two alternative spatial weight specifications

Statistic	$I(\mathbf{W}_{S,10})$	$I(\mathbf{W}_{G,10})$
$\%Belief_c$	0.550***	0.508***
	(0.000)	(0.000)
$\%Risk_c$	0.598***	0.553***
	(0.000)	(0.000)
$HealthImpact_{30,c}$	0.101***	0.094***
	(0.000)	(0.000)
$AssetImpact_{30,c}$	0.235***	0.273***
	(0.000)	(0.000)
$TMax_c$	0.529***	0.450***
	(0.000)	(0.000)
$High2016_c$	0.526***	0.451***
	(0.000)	(0.000)
$Low2016_c$	0.495***	0.426***
	(0.000)	(0.000)
$\%Bachelor_c$	0.435***	0.410***
	(0.000)	(0.000)
$\%OilGasMining_c$	0.416***	0.400***
	(0.000)	(0.000)

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

as predictor variables in the multi-level regression and post-stratification (MRP) process deployed by Howe et al. (2015). Subsequent empirical specifications relating these variables at the county-level would simply recover coefficient estimates which are reflective of (but, due to differences in the unit of observation, do not exactly coincide with) the coefficient estimates obtained from the statistical model estimated by Howe et al. (2015). However, despite this limitation, alternative hypotheses can be explored using these survey-based estimates contingent on two conditions being met. First, the variables of interest must not have been included as covariates in the statistical model estimated by Howe et al. (2015), and second, the effects of these variables must have been captured in the county fixed effects included in their model as a control for unobserved county-level variation. Just as Kaufmann et al. (2017) argue that the county-level temperature heuristics that they propose meet these criteria, so too do we for county-level climate heuristics related to extreme weather.

2.2. **Measuring a County's Historical Extreme Weather Exposure.** We obtain data on the date, affected locations, and impacts of extreme weather events in the United States between 1960 and 2021 from the Spatial Hazard Events and Losses Dataset for the United States (SHELDUS) (ASU Center for Emergency Management and Homeland Security (2023)).

We use this data to construct heuristics which describe two salient aspects of a county's historical exposure to extreme weather: adverse health outcomes and damages to physical assets.

For the first heuristic, we focus our attention on the number of injuries and fatalities attributable to extreme weather within each county. We first query SHELDUS to access aggregate injury and fatality statistics by county c and year t. To consolidate these into a single measure, we treat one injury as equivalent to one-tenth of a fatality, consistent with the approach employed by the United States Federal Emergency Management Agency (FEMA) in the calculation of the National Risk Index (Zuzak et al. (2022)). We then define the set $\mathbf{H}$ as the h years preceding the measurement of our dependent variable and calculate the heuristic $HealthImpact_{h,c}$ as follows:

$$HealthImpact_{h,c} = \frac{\sum\limits_{t \in \mathbf{H}} HealthImpact_{c,t}}{h} \tag{1}$$

A unit increase in $HealthImpact_{h,c}$ is equivalent to 1 additional fatality or 10 additional injuries per year, averaged over the preceding h years.

The second heuristic, $AssetImpact_{c,h}$, measures the average annual value of extreme-weather related crop and property damages (in millions of constant 2021 US dollars) over the preceding h years. We begin by querying SHELDUS to access crop and property damage statistics by county c and year t (denoted $AssetImpact_{c,t}$) before calculating the heuristic $AssetImpact_{h,c}$ as follows:

$$AssetImpact_{h,c} = \frac{\sum\limits_{t \in \mathbf{H}} AssetImpact_{c,t}}{h} \tag{2}$$

A unit increase in $AssetImpact_{h,c}$ is equivalent to an additional \$1 million in extreme weather-related crop and property damages annually, averaged over the preceding h years.

While these heuristics are constructed to describe two important aspects a county's historical exposure to extreme weather, the horizon over which individuals assimilate these experiences is unclear. We thus calculate these heuristics over three horizons (h = 20, 30, and 40 years), adopting the 30-year horizon as our baseline specification and evaluating the robustness of our results across these horizons.

Summary statistics for $HealthImpact_{30,c}$ and $AssetImpact_{30,c}$ are presented in Table 1. On average, counties experience the equivalent of 0.3 extreme weather-related fatalities ($HealthImpact_{30,c}$) and \$9.4 million in property and crop damages ($AssetImpact_{30,c}$) per year. However, the median values for both heuristics are significantly lower – 0.107 for $HealthImpact_{30,c}$ and \$1.546 million for $AssetImpact_{30,c}$ – indicating that a relatively small number of counties face disproportionately large impacts. This observation is further reinforced by the maximum values of each heuristic, with some counties experiencing the equivalent of 38.166 extreme weather-related fatalities or $1.28 billion in damages annually. The skewed nature of counties' historical exposure to extreme weather is reflective of spatial heterogeneities in the frequency, types, and severity of extreme weather events, as well as variations in county characteristics such as population, landmass, and economic activity. These disparities underscore the importance of accounting for heteroskedasticity in our empirical strategy, as is discussed further in Section 3.

Both extreme weather heuristics also exhibit significant spatial clustering, as indicated by Moran's I (Table 2). Positive and statistically significant Moran's I test statistic values for both $HealthImpact_{30,c}$ and $AssetImpact_{30,c}$ suggest that counties with higher or lower rates of extreme weather-related injuries and fatalities and damages are likely to be geographically or socially proximate. These patterns are reflective of the regional scale of extreme weather events such as hurricanes and droughts and highlight the need to explicitly account for spatial dependence in our empirical strategy.

2.3. **Temperature Data.** In order to assess the role of extreme weather in shaping climate opinion independent of (and relative to) changes in temperature, we reconstruct the heuristics for local changes in temperature proposed by Kaufmann et al. (2017) using more recent data. As outlined in Appendix A.2, these heuristics describe local changes in temperature based on the relative timing of record high and low temperatures and were found to partially account for the observed spatial variation of climate change beliefs at the US county level.

To calculate the heuristics, we obtain data on daily high and low temperatures for 69,604 weather stations in the United States from the Global Historical Climatology Network - Daily (GHCN-d) database (Menne et al. (2012)). Because the number of years for which data are available and the number of missing observations affect the heuristic values, we classify each station by these variables and retain only those with a minimum of 40 years of data and at most 10 missing observations. This is consistent with an intermediate case in Kaufmann et al. (2017), who demonstrated the robustness of their results to alternative horizons and missing value thresholds.

The heuristics for local changes in temperature are then calculated for each weather station s in our sample as follows:

$$TMax_s = \sum_{D=1}^{365} \mathbb{1}_{(High_{Ds} > Low_{Ds})} \tag{3}$$

$$High2016_s = \sum_{D=1}^{365} [\mathbb{1}_{(High_{Ds} > Low_{Ds})} \times \mathbb{1}_{(High_{Ds} \geq 2016)}] \tag{4}$$

$$Low2016_s = \sum_{D=1}^{365} [\mathbb{1}_{(Low_{Ds} > High_{Ds})} \times \mathbb{1}_{(Low_{Ds} \geq 2016)}] \tag{5}$$

where D denotes the day of the year, $High_{Ds}$ and Low_{Ds} denote the years of the record high and low temperatures on day D at station s, and $\mathbb{1}$ denotes an indicator function. Station-level heuristic values are then mapped to US counties in geographical information system (GIS) software using the method described in Appendix B.2.

$TMax_c$ measures the local change in climate in county c as the number of days of the year for which the year of the record high temperature is more recent than the year of the record low temperature. A value of 182 thus signifies no change in temperature, whereas smaller and larger values connote local cooling and warming, respectively. Because of its clever construction, this heuristic has attractive distributional properties under the null hypothesis of a non-changing climate. Specifically, under this null hypothesis there is an equal probability that, for a given day of the year, the record high temperature or the record low temperature will have occurred most recently. Summing over 365 days, the distribution of $TMax_c$ in the sample is thus expected to coincide with the binomial distribution ($n = 365$, $p = 0.5$) under the null. However, as illustrated in Figure 3, this is not the case for the observed distribution of $TMax_c$. On the one hand, more counties exhibit values of $TMax_c$ which are indicative of a warming climate than would be expected under random chance. For example, while only 0.5% of the counties are expected to observe $TMax_c$ values greater than 207 in a non-changing climate, 47.1% of counties do so in our sample. On the other hand and much more surprisingly, many other counties exhibit evidence of local cooling. 8% of counties exhibit $TMax_c$ values of less than 157 in our sample, a threshold past which only 0.5% of counties would be expected to fall below by chance in a non-changing climate. These observations are consistent with those of Kaufmann et al. (2017), although they signify a marginal distributional shift toward more local warming.

$High2016_c$ and $Low2016_c$ then differentiate themselves from $TMax_c$ by measuring the *recency* of local warming and cooling. They do so as simple counts of the number of days for which record high and low temperatures are observed in the five years preceding the measurement of our dependent variable. Similar to Kaufmann et al. (2017), the mean values of $High2016_c$ (23.195) and $Low2016_c$ (10.371) suggests record high temperatures are more than twice as likely to occur than record low temperatures on average in the past five years. Summary statistics can be found in Table 1. We also note that Moran's I test statistics for $TMax_c$, $High2016_c$, and $Low2016_c$ are indicative of significant positive spatial autocorrelation (see Table 2), with spatial heterogeneity and clustering clearly visible in Figure 4.

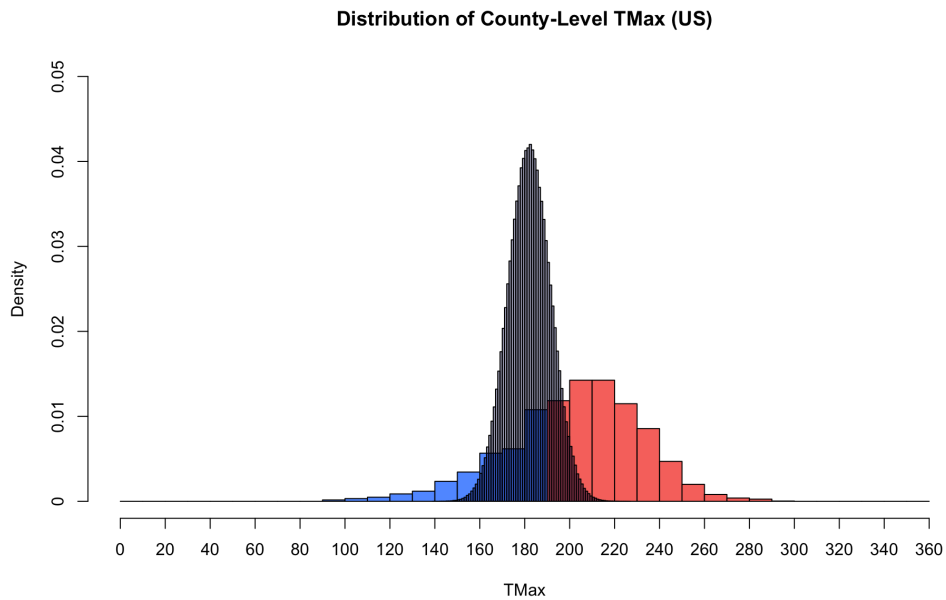

Figure 3. A histogram of observed county-level TMax values $(TMax_c)$ is plotted against the fraction of observations for a given level of TMax expected under the null hypothesis of no climate change. Areas in red represent the fraction of stations where TMax indicates warming, whereas areas in blue represent the fraction of stations where TMax indicates cooling. We note that more stations exhibit TMax values consistent with both local warming and local cooling than anticipated under the null hypothesis of a non-changing climate.

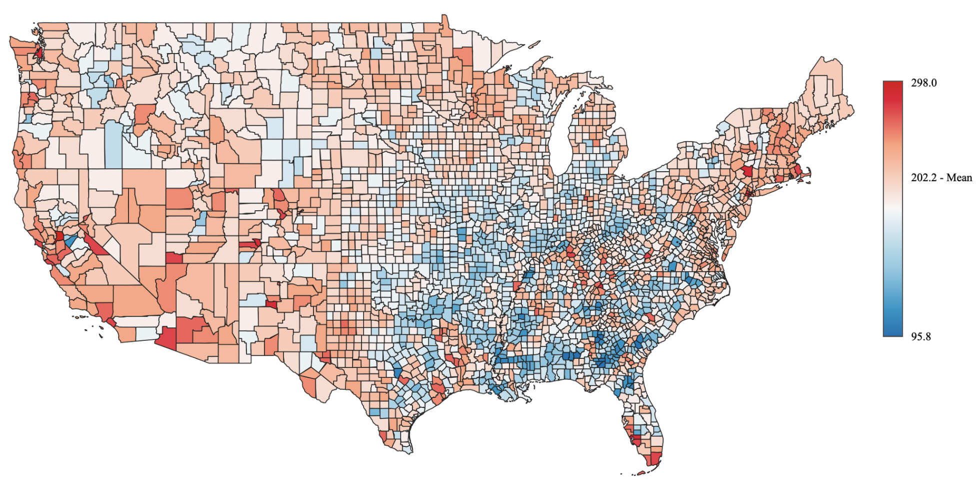

Figure 4. County-level variation in $TMax_c$

2.4. **Controls Data.** As discussed in Appendix A.2, previous research has established a robust relationship between climate opinion and individual-level covariates such as educational attainment and industry of employment. In alignment with this evidence, these variables were incorporated by Howe et al. (2015) to construct the county-level climate opinion estimates used in this study (see Section 2.1 and Appendix B.1 for more details). We thus source data on these variables at the county level in order to include them as controls in our empirical specification. We obtain data on educational attainment from the 2021 American Community Survey through the US Census Bureau (accessed September 10, 2023), defining $\%Bachelor_c$ as the percentage of the adult population in county c which has completed a Bachelor's degree or higher. For industry of employment, we define $\%OilGasMining_c$ as the percentage of the county's total labour force employed either full- or part-time in the mining, quarrying, and oil and gas extraction sector (as categorized by the North American Industry Classification System). This data is sourced from the US Bureau of Economic Activity (accessed September 10, 2023). Summary statistics and Moran's I test statistic values for these variables are included in Tables 1 and 2, respectively.

2.5. **Modeling the Interaction Between Observational Units.** As discussed in Section 1, spatial dependence may arise in county-level climate opinion formation for a variety of reasons and results in challenges with statistical inference. Spatial econometrics – introduced by Paelinck and Klaassen (1979), advanced by Anselin (1988), and summarized more recently by LeSage and Pace (2009) – was established to address these challenges and one of its defining features is the explicit modeling of the neighbour relation. The neighbour relation between n observational units is represented by an $n \times n$ matrix $\mathbf{W}$, where each element defines the relative influence or proximity between two observational units. This matrix is used to construct spatially lagged dependent ($\mathbf{W}y$) and independent ($\mathbf{W}X$) variables, and plays a critical role in spatial econometrics. Moreover, spatial weight matrices are foundational to a variety of specification tests, including Moran's I (Moran (1948), Moran (1950)) and Anselin's lagrange multiplier test statistics (Anselin et al. (1996)), which are essential for identifying and quantifying spatial dependence in this setting.

But how does one determine which neighbour specification to use? This is an important lingering question and crucial shortcoming in the spatial econometrics literature (Leenders (2002), Elhorst (2010)). While approaches to assist with the ex ante selection of a spatial weight specification would be a welcome addition to the literature, no methods have gained widespread acceptance to date. Instead, it is common practice to select the optimal spatial weight specification based on a goodness-of-fit criteria ex-post (Stakhovych and Bijmolt (2009)) and evaluate the robustness of one's results to alternative spatial weight specifications (Ertur and Koch (2007)). In this paper, we adopt this approach by constructing an extensive set of spatial weight matrices, denoted by $\mathbb{W}$, and incorporating them into the model selection framework described in Section 3.

Spatial weight matrices based on the geographic distance between observational units are standard in the literature, as noted by LeSage and Pace (2009). Building on the approach by Kaufmann et al. (2017), who focus on a 5-nearest neighbour spatial weight specification in their study of how local changes in temperature shape climate opinion at the US county level, we construct k-nearest neighbour weight specifications for $k = 1, ..., 500$. As the name suggests, these spatial weight matrices define the neighbour relation by connecting each observational unit to its k-nearest geographic neighbours, as measured by Euclidean distance between the centroids of observational units. For an $n \times n$ matrix $\mathbf{W}$, the $(i, j)^{th}$ element of $\mathbf{W}$ $(w_{i,j})$ equals 1 if county j is among the k-nearest neighbours of county i and 0 otherwise. This matrix is then typically row-standardized such that $\sum_{j=1}^{n} w_{i,j} = 1 \; \forall \; i \in (1, ..., n)$, resulting in the attractive property that the spatial lag $\mathbf{W}Z$ can be interpreted as the average value of the variable Z in the neighbouring counties (as defined by $\mathbf{W}$). To construct these k-nearest neighbour spatial weight matrices, we first obtain cartographic boundary files for US counties (2021 delineation) from the US Census Bureau (accessed September 10, 2023) and extract the coordinates of the centroid of each county in QGIS[3]. The resulting coordinates were then used to compute weight matrices for $k = 1, ..., 500$ as described above using the *knn2nb* function in R's *spdep* package.

LeSage and Pace (2009) also note, however, that the concept of a spatial weight matrix can be generalized to account for non-spatial structured dependence. This approach has been used to study peer institution effects in wage setting (Blankmeyer et al. (2007)) and coordination amongst socially-connected peers in a non-cooperative game (Ballester et al. (2006)), and is closely aligned with the Katz-Bonacich Centrality (Katz (1953), Bonacich (1987)) in the social networking literature. Motivated by the strong theoretical (Bandura (1977)) and experimental (Moussaïd et al. (2013)) basis for social influence in the climate opinion formation process, we therefore supplement the set of more typical spatial weight matrices based on geographic distance with a set based on a measure of social distance. To define the social distance between US counties, we leverage Data for Good's Social Connectedness Index (Bailey et al. (2018)). It is defined as follows:

$$Social_{ij} = \frac{Connections_{i,j}}{Users_i \times Users_j} \tag{6}$$

where $Connections_{i,j}$ is the total number of Facebook connections between users in counties i and j and $Users_k$ is the number of Facebook users in county k in October 2021. The Social Connectedness Index – scaled between 1 and 1,000,000,000 – measures the relative probability of a Facebook friendship between users in counties i and j. For example, if $Social_{i,j}$ is twice as large as $Social_{i,k}$, then a Facebook user in county i is twice as likely to be connected with a user in county j than in county k. To construct spatial weight matrices based on this measure, we first construct an $n \times n$ matrix such that element $w_{i,j} = Social_{i,j}$ for $j \neq i$ and zero otherwise. We then truncate this matrix such that $w_{i,j} = 0$ if county j

[3]QGIS is a free geographic information system software that can be accessed at www.QGIS.org.

is not one of county i's k-nearest social neighbours, doing so for $k \in (1, ..., 500)$. Finally, we divide each element by its row sum such that $\sum_{j=1}^{n} w_{i,j} = 1 \; \forall \; i \in (1, ..., n)$, denoting the resulting matrices by $\mathbf{W}_{S,k}$. The spatial lag $\mathbf{W}_{S,k}Z$ can thus be interpreted as the weighted average of Z in its k nearest social neighbours.

3. Empirical Strategy

Bearing in mind the theoretical and empirical basis for spatial dependence discussed in Section 1 and Appendix A, we leverage empirical tools from the spatial econometrics literature to assess the relationship between US county-level climate opinion and the consequences of extreme weather.

First, we estimate our specifications of interest under the assumption of cross sectional independence and assess whether this assumption is valid. To do so, we begin by estimating the following non-spatial specifications by ordinary least squares (OLS):

$$y = X\beta + u \tag{7}$$

in which y is a vector of either county-level climate beliefs ($\%Belief$) or risk perceptions ($\%Risk$) as defined in Section 2.1 and X is a matrix containing various combinations of extreme weather heuristics (as defined in Section 2.2), temperature heuristics (as proposed by Kaufmann et al. (2017) and defined in Section 2.3), and educational and industry controls (as defined in Section 2.4). β is a vector of regression coefficients and u is a vector of regression errors. We then test the null hypothesis of no residual spatial autocorrelation using Moran's I for regression residuals (Moran (1950); Cliff and Ord (1972)):

$$Moran's\ I \ = \ \frac{n}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}} \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(\hat{u}_i - \bar{\hat{u}})(\hat{u}_j - \bar{\hat{u}})}{\sum_{i=1}^{n}(\hat{u}_i - \bar{\hat{u}})^2} \tag{8}$$

where w_{ij} is the ij^{th} element of a spatial weight matrix W, $\hat{u}_i$ are regression residuals from the estimation of equation (7) by OLS, and $\bar{\hat{u}}$ is equal to $\sum_{i=1}^{n} \hat{u}_i/n$. This specification test is conducted for the set of spatial weight matrices $\mathbb{W}$ defined in Section 2.5, and we define $\mathbb{W}^0$ as the subset of spatial weight matrices in $\mathbb{W}$ for which we reject the null hypothesis ($p < 0.1$). The asymptotic distribution of the test statistic is standard normal after subtracting the mean of the regression residuals and dividing by the standard deviation (Cliff and Ord (1981)). If $\mathbb{W}^0$ is empty, we proceed with the OLS estimates.

Second, if $\mathbb{W}^0$ is non-empty, we proceed to select the optimal spatial weight matrix W^*. This selection is based on an ex-post goodness-of-fit criteria which simulation-based evidence has shown increases the probability of finding the true weight specification (Stakhovych and Bijmolt (2009)). To do so, we begin by estimating a spatial Durbin specification (Anselin (1988)) by maximum likelihood for each spatial weight matrix in $\mathbb{W}^0$. The spatial Durbin specification extends the non-spatial specifications defined in equation (7) to include spatial lags of both the dependent (Wy) and independent[4] (WX) variables:

$$y = \rho Wy + X\beta + WX\theta + u \tag{9}$$

For each of the spatial Durbin specifications estimated, we then test the null hypothesis of no residual spatial autocorrelation using Moran's I for regression residuals and define $\mathbb{W}^1$ as the subset of spatial weight matrices in $\mathbb{W}^0$ for which we do not fail to reject the null hypothesis ($p \geq 0.10$). Finally, amongst the spatial weight matrices in $\mathbb{W}^1$, we select the optimal spatial weight matrix W^* as the spatial weight matrix whose affiliated Spatial Durbin specification exhibits the largest pseudo-R^2 value (Nagelkerke (1991)).

Third, having selected the optimal spatial weight matrix W^*, we proceed to assess whether the Spatial Durbin specification can be pared down to a more parsimonious specification. To do so, we employ likelihood ratio (LR) tests to evaluate null hypotheses coinciding with two nested alternatives. The null hypothesis $\theta = 0$ coincides with a spatial lag specification:

$$y = \rho Wy + X\beta + u \tag{10}$$

and the null hypothesis $\theta + \rho\beta = 0$ coincides with a spatial error specification:

$$y = X\beta + u, \quad where \quad u = \lambda Wu + \epsilon \tag{11}$$

If both null hypotheses are rejected, we conclude that the spatial Durbin specification best describes the data. If only one of these null hypotheses is rejected, we adopt the specification coinciding with the null hypotheses which we fail to reject. If we fail to reject both null hypotheses, we construct robust Lagrange multiplier (LM) test statistics (Anselin et al. (1996)) for both specifications and select the specification with the larger LM test statistic. These test statistics test for spatial autocorrelation in regression residuals from the estimation of equation (7) and specify the spatial lag and spatial error models as explicit alternatives:

$$LM_{lag} = \frac{\left(\frac{\hat{u}'Wy}{\hat{u}'\hat{u}/n}\right)^2}{D} \overset{a}{\sim} \chi^2_1 \tag{12}$$

[4]We note that we omit spatial lags of our controls due to the absence of a theoretical basis for these effects.

$$LM_{error} = \frac{(\frac{\hat{u}'W\hat{u}}{\hat{u}'\hat{u}/n})^2}{T} \overset{a}{\sim} \chi^2_1 \tag{13}$$

where $D = [\frac{(WX\hat{\beta})'(I-X(X'X)^{-1}X')(WX\hat{\beta})}{(\hat{u}'\hat{u}/n)}] + tr(W^2 + W'W)$ and $T = tr(WW + W'W)$.

Fourth, we test for heteroskedasticity in the residuals of the preferred specification using the Breusch-Pagan test (Breusch and Pagan (1979)). If we fail to reject the null hypothesis ($p \geq 0.10$), we proceed with our initial maximum likelihood estimates. However, if we reject the null hypothesis ($p < 0.10$), we proceed to estimate the preferred specification using the multi-step GMM/IV estimation procedure proposed by Kelejian and Prucha (2010) and generalized by Arraiz et al. (2010). Crucially, and in contrast to the maximum likelihood estimators that are most commonly used in this literature[5], using this GMM/IV estimation procedure allows the error term u to be heteroskedastic of an unknown form.

And fifth, if the preferred specification resulting from this estimation procedure contains a spatial lag of the dependent variable ($\rho \neq 0$), we construct the summary impact measures proposed by Pace and LeSage (2006). These measures were devised to overcome challenges with coefficient interpretation borne out of the expansion of the information set to include neighbour effects. In this setting, the partial derivative of y with respect to x_k is no longer equal to the scalar $\hat{\beta}_k$, but is rather an $n \times n$ matrix with elements that are functions of the coefficient estimates ρ, β_k, and θ_k and the spatial weight matrix W:

$$\frac{\partial y}{\partial x_k} = S_k(W) \tag{14}$$

where $S_k(W) = V(W)(I\beta_k + W\theta_k)$ and $V(W) = (I - \rho W)^{-1}$ [see Appendix B.3 for additional information]. The average direct effect (ADE) – equal to the sum of the diagonal elements of $S_k(W)$ divided by n – has a similar interpretation to β_k in non-spatial specifications, capturing the effect of a unit increase in $x_{k,i}$ on the outcome y_i, holding outcomes in all other counties constant. By contrast, the average indirect effect (AIE) is a measure of spatial spillovers. It is equal to the sum of the off-diagonal elements of $S_k(W)$ divided by $n(n-1)$ and can be interpreted as either the cumulative effect of a unit increase in x_k in observational unit i on the outcome y in all other observational units $j \neq i$ (termed the *Average Indirect Effect To*) or as the effect of a simultaneous unit increase in x_k in all other observational units $j \neq i$ on the outcome y in observational unit i (termed the *Average Indirect Effect From*). These interpretations are mathematically equivalent (LeSage and Pace (2009)). Standard errors, z-statistics, and p-values are constructed for the summary impact measures by Monte Carlo simulation.

[5]For example, Kaufmann et al. (2017) estimate a spatial lag specification by maximum likelihood to evaluate the role of temperature in shaping climate opinion.

3.1. **Robustness Checks.** We demonstrate the robustness of our results in two ways. First, we assess their sensitivity to alternative spatial weight specifications. This approach arose in the spatial econometrics literature in response to concerns regarding the sensitivity of coefficient estimates derived from the spatial lag and spatial Durbin specifications to the choice of the spatial weight matrix (Gibbons and Overman (2012)). Despite LeSage and Pace (2014) largely dispelling these concerns, this approach remains commonplace in empirical research. As a point of comparison, we therefore repeat the estimation procedure outlined in Section 4.2 using two alternative methods for selecting the optimal spatial weight matrix W^*. The first method involves selecting the spatial weight matrix which most effectively controls for residual spatial autocorrelation. This involves estimating the Spatial Durbin specification in equation (9) for each $W \in \mathbb{W}^0$ and selecting the specification whose Moran's I test statistic exhibits the largest p-value. The second method involves selecting the most parsimonious spatial weight matrix in $\mathbb{W}^1$ (i.e., amongst those whose affiliated Spatial Durbin specifications fail to reject the null hypothesis of no residual spatial autocorrelation ($p \geq 0.10$) based on Moran's I for regression residuals). In this context, the parsimony of a spatial weight matrix W is evaluated based on its relative sparsity. If spatial weight matrices based on social and geographic distance are equally sparse (parsimonious), we use the goodness-of-fit criteria described in Section 3 as a tie-breaker.

And second, we demonstrate the robustness of our results to the horizon over which we calculate the extreme weather heuristics outlined in Section 2.2. While we postulate that county-level climate opinion is shaped in part by counties' historical exposures to extreme weather-related losses, the horizon over which county residents assimilate these experiences is unclear. We therefore calculate these heuristics over three alternative horizons: 20, 30, and 40 years. This approach is also applied by Kaufmann et al. (2017), who demonstrate that the relationship between county-level climate opinion and their temperature heuristics is robust across multiple time horizons.

4. Results

4.1. **OLS Results and Evidence of Residual Spatial Autocorrelation.** Results from the estimation of equation (7) for the dependent variables $\%Belief$ and $\%Risk$ are reported in Tables 3a and 3b, respectively. Taken at face value, these coefficient estimates support the hypotheses that residents of counties that experience more severe extreme weather – as measured by historical adverse health impacts ($HealthImpact$) and property damages ($AssetImpact$) – are more likely to believe that climate change is happening and that it will harm them personally in the future. This result holds in the presence of well-established industry and educational controls, as well as the temperature heuristics proposed by Kaufmann et al. (2017). However, based on Moran's I for regression residuals, there is strong evidence of (positive) residual spatial autocorrelation in each of these specifications ($p < 0.01$). As noted in Section 1, this will result in biased and inconsistent coefficient estimates. We therefore proceed with the spatial econometric estimation procedure outlined in Section 3.

4.2. **Spatial Econometric Estimation Results.**

4.2.1. *Model Selection.* The results of the model selection procedure for the dependent variables $\%Belief$ and $\%Risk$ are presented in Tables 4a and 4b, respectively. There are five observations of note. First, based on Moran's I for regression residuals, the procedure was effective in eliminating evidence of residual spatial autocorrelation in all eight specifications of interest ($p \geq 0.10$). Second, the spatial Durbin model (Equation 9) was universally selected as the preferred spatial econometric specification based on likelihood ratio tests ($p < 0.10$). This indicates that spatial lags of both the dependent and independent variables are important components of the data generating process for climate opinion at the US county level. Third, social distance was preferred to geographic distance in the selection of an optimal spatial weight matrix across all eight specifications of interest. This result is consistent with social learning theory (Bandura (1977)) and experimental evidence of peer effects in the opinion formation process (Moussaïd et al. (2013)), suggesting that social distance more accurately reflects the flow and influence of information between US counties than geographic distance in the context of this study. It also supports the assertion of Howe et al. (2019) that empirical research into climate opinion would benefit from greater integration with psychological theories. Fourth, the optimal spatial weight matrices are notably more sparse in models of climate risk perceptions (see Table 4b) than in models of climate beliefs (see Table 4a). While this observation is insufficient to comment on the magnitude of spatial spillovers, it does imply that spillovers are more extensive – in terms of the number of peers that they extend to – in the formation of climate beliefs than in the formation of climate risk perceptions. And fifth, we obtain evidence of heteroskedasticity in the maximum likelihood estimation results for all eight specifications of interest based on the Breusch-Pagan test (Breusch and Pagan (1979)). This is unsurprising in light of the significant county-level heterogeneities discussed in Section 2. As a result, we adopt a GMM/IV estimator with heteroskedastic innovations (Kelejian and Prucha (2010), Arraiz et al. (2010)) to avoid potential biases and inefficiencies associated with maximum likelihood estimation in this setting.

4.2.2. *The Direct Effect of Experiential Learning.* Estimates of the average direct effect of extreme weather and temperature heuristics on climate beliefs and risk perceptions are presented in Panel A of Tables 5a and 5b, respectively. These estimates support the hypothesis that climate opinion is shaped in part by individuals' experiences with their local weather and climate.

First, we find that residents of counties that experience more severe extreme weather are more likely to believe that climate change is happening and that it will harm them personally in the future. On average, a unit increase in $HealthImpact_i$ (equivalent to 1 additional fatality or 10 additional injuries per year in county i that are attributable to extreme weather) results in 0.455 and 0.653 percentage point increases in $\%Belief_i$ and $\%Risk_i$, respectively. We also obtain positive and statistically significant average direct effect estimates for $AssetImpact_i$, with an additional \$1 million in extreme weather-related property or crop damages per year associated with 0.003 and 0.006 percentage point increases in $\%Belief_i$ and $\%Risk_i$, respectively (see column (2) of Tables 5a and 5b). However, these effects are dominated by those of $HealthImpact_i$ and the temperature heuristics of Kaufmann et al. (2017) when estimated jointly (see column (4) of Tables 5a and 5b). These findings hold in the presence of well-established industry and educational controls.

Second, these results reinforce the finding of Kaufmann et al. (2017) that local temperatures influence climate opinion at the US county level. In column (3) of Table 5a, we show that their primary results – that local warming (as proxied by $TMax$) increases the public's willingness to believe global warming is happening, but that these effects are dampened by recent record low temperatures ($Low2016$) in counties that warmed ($TMax > 182$) over the sample period (40 years) – hold under a more general spatial econometric estimation procedure[6] and on more recent data. We also show in columns (3) and (4) of Table 5a that, for the outcome $\%Belief$, their results hold over and above the effects of extreme weather, local industry, and educational attainment. However, we note that their results do not extend to the outcome $\%Risk$[7] (see columns (3) and (4) of Table 5b), thus highlighting a critical difference between temperature- and extreme weather-based experiences and their role in shaping climate opinion.

And third, these results suggest that exposure to extreme weather may be more influential in shaping climate opinion than local temperatures, particularly when it results in injuries or fatalities. Based on these estimates, a one standard deviation (SD) increase in $HealthImpact_i$ results in 0.09 SD (or 0.53 percentage point) and 0.15 SD (or 0.76 percentage point) increases in $\%Belief_i$ and $\%Risk_i$, respectively. These impacts are two to three times larger than those of $AssetImpact_i$ and $TMax_i$, with a one SD increase in the former associated with a 0.03 SD (0.06 SD) increase in $\%Belief_i$ ($\%Risk_i$) and a one SD increase in the latter associated with a 0.04 SD increase in $\%Belief_i$ (but no statistically significant increase in $\%Risk_i$).

[6] Kaufmann et al. (2017) restrict their attention to a five nearest neighbour spatial weight specification based on geographic distance and a spatial lag model specification.

[7] Kaufmann et al. (2017) did not study the relationship between their proposed temperature heuristics and risk perceptions, focusing only on climate change beliefs.

4.2.3. *Spatial Spillovers in the Climate Opinion Formation Process.* Estimates of the average indirect effect of extreme weather and temperature heuristics on climate beliefs and risk perceptions can be found in Panel B of Tables 5a and 5b, respectively. In the case of climate beliefs, we obtain robust evidence that local weather in county i not only results in direct (i.e., experiential learning) effects on $\%Belief$ in county i, but also indirect effects (i.e., spatial spillovers) on $\%Belief$ in counties $j \neq i$. For example, under the *Average Indirect Effect To* interpretation, unit increases in $HealthImpact$ and $AssetImpact$ in county i would result in a cumulative impact on $\%Belief$ in counties $j \neq i$ of 4.766 and 0.066 percentage points, respectively (see columns (1) and (2) of Table 5a). Alternatively, under the mathematically equivalent *Average Indirect Effect From* interpretation, unit increases in $HealthImpact$ and $AssetImpact$ in all counties $j \neq i$ would result in $\%Belief$ in county i increasing by 4.766 and 0.066 percentage points, respectively. We note that these effects extend to recent record low temperatures (see column (3) of Table 5a), and that the effects of $HealthImpact$ dominate those of $AssetImpact$ when estimated jointly (see column (4) of Table 5a).

By contrast, we obtain much more limited evidence of spatial spillovers in the formation of climate risk perceptions. While estimates in column (1) of Table 5b suggest that extreme weather-related injuries and fatalities in county i spill over into risk perceptions in counties $j \neq i$, this effect becomes statistically insignificant when estimated jointly with other experiential cues (see column (4) of Table 5b). These estimates therefore point towards an important distinction between the processes that govern climate beliefs and risk perceptions. While simply increasing awareness of extreme weather in other parts of the country is enough to increase beliefs that climate change is happening, personal experience may be necessary for an individual to become concerned for their own safety and well-being.

If elevated risk perceptions are critical to sparking adaptive planning (as is discussed for example, in Jabeen and Johnson (2013)), this observation could have important implications for disaster preparedness across the United States. In the absence of spatial spillovers, elevated risk perceptions are more likely to be concentrated in regions with high historical exposures to extreme weather. However, attribution studies are beginning to shed light on how climate change is altering extreme weather patterns in the United States. For example, climate change is understood to have increased the frequency and severity of some types of extreme weather (Peterson et al. (2013), Seager et al. (2015), Wang et al. (2015), Herring et al. (2015), Eden et al. (2016)) and decreased the frequency and severity of others (Trenary et al. (2016), Huang et al. (2018). Herring et al. (2021)). These shifting patterns – which imply that a county's historical exposure to extreme weather may not always be a strong predictor of its exposure in the future – could contribute to counties being either over- or under-prepared for future risks, potentially misallocating resources in the process.

4.3. **Robustness.** Table 6 demonstrates the robustness of our estimation results to alternative methods for selecting the optimal spatial weight matrix W^*. Average direct impact estimates for $HealthImpact$ remain positive and statistically significant when selecting W^* in order to minimize Moran's I (see columns (2) and (5)) or to eliminate evidence of residual spatial autocorrelation in the most parsimonious way possible (see columns (3) and (6)). They also further support the observation that spatial spillovers arise in the formation of climate beliefs (see columns (1)-(3)), but not risk perceptions (see columns (4)-(6)). Together, these estimates suggestive that our results are robust in a qualitative sense. However, we do note that these results challenge the quantitative robustness of the average indirect effect estimates in our main results, with the alternative methods resulting in the selection of more sparse spatial weight matrices and, in turn, average indirect effects for $HealthImpact$ that are of a smaller magnitude. This occurs because, as demonstrated in Appendix (B.3), the summary impact measures proposed by Pace and LeSage (2006) are a function of the spatial weight matrix W. Despite this observation, we maintain goodness-of-fit as our preferred method for selecting the optimal spatial weight matrix as it is standard practice in the spatial econometrics literature and supported by simulation-based evidence from Stakhovych and Bijmolt (2009).

Our results are also robust to extreme weather impacts calculated over alternative horizons, as illustrated by Table 7. Direct experiential learning effects associated with $HealthImpact$ are observed for both $\%Belief$ and $\%Risk$ over 20, 30, and 40 year horizons, with personal experience consistently exerting a greater influence on climate risk perceptions than climate beliefs. Consistent with our main findings, we also observe spatial spillovers in the formation of climate beliefs across each of these horizons (see columns (1)-(3)), but not in the formation of climate risk perceptions.

Table 3a. OLS Results - %Belief

	%Belief			
	(1)	(2)	(3)	(4)
HealthImpact	0.523***			0.474***
	(0.077)			(0.081)
AssetImpact		0.006***		0.001
		(0.002)		(0.002)
TMax			0.027***	0.026***
			(0.004)	(0.004)
High2016 × ($TMax \leq 163$)			0.037	0.036
			(0.024)	(0.024)
High2016 × ($163 < TMax \leq 182$)			-0.002	-0.003
			(0.016)	(0.0016)
Low2016 × ($182 < TMax \leq 201$)			-0.065***	-0.061***
			(0.019)	(0.018)
Low2016 × ($201 < TMax$)			-0.058***	-0.051***
			(0.016)	(0.016)
(Intercept)	57.388***	57.314***	52.537***	52.869***
	(0.230)	(0.230)	(0.903)	(0.900)
Controls	Yes	Yes	Yes	Yes
Observations	3,108	3,108	3,108	3,108
R^2	0.365	0.358	0.368	0.376
Moran(W*)	0.378***	0.382***	0.371***	0.361***

Note 1: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Table 3b. OLS Results - %Risk

	%Risk			
	(1)	(2)	(3)	(4)
HealthImpact	0.743***			0.635***
	(0.073)			(0.077)
AssetImpact		0.011***		0.005***
		(0.002)		(0.002)
TMax			0.029***	0.026***
			(0.004)	(0.004)
High2016 × ($TMax \leq 163$)			0.086***	0.084***
			(0.023)	(0.023)
High2016 × ($163 < TMax \leq 182$)			0.013	0.011
			(0.015)	(0.015)
Low2016 × ($182 < TMax \leq 201$)			-0.050***	-0.042**
			(0.018)	(0.018)
Low2016 × ($201 < TMax$)			-0.030*	-0.016
			(0.015)	(0.015)
(Intercept)	37.306***	37.211***	31.814***	32.414***
	(0.219)	(0.220)	(0.866)	(0.856)
Controls	Yes	Yes	Yes	Yes
Observations	3,108	3,108	3,108	3,108
R^2	0.149	0.134	0.142	0.170
Moran(W*)	0.548***	0.548***	0.539***	0.535***

Note: $^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Table 4a. Model Selection Results - %Belief

	%Belief			
	(1)	(2)	(3)	(4)
Panel A: Selection Criteria				
Pseudo-R^2	0.622	0.616	0.617	0.625
Moran's I	0.007	0.008	0.007	0.008
LR_{lag}	59.635***	56.397***	63.635***	70.117***
LR_{error}	57.008***	47.693***	51.002***	70.791***
Breusch-Pagan	29.369***	27.673***	34.310***	51.603***
Panel B: Selection Results				
Weight Specification	$W_{S,328}$	$W_{S,250}$	$W_{S,274}$	$W_{S,449}$
Model Specification	SDM	SDM	SDM	SDM
Estimator	GMM/IV	GMM/IV	GMM/IV	GMM/IV

Table 4b. Model Selection Results - %Risk

	%Risk			
	(1)	(2)	(3)	(4)
Panel A: Selection Criteria				
Pseudo-R^2	0.590	0.574	0.573	0.592
Moran's I	0.008	0.008	0.008	0.008
LR_{lag}	13.01***	12.131***	16.882**	19.213**
LR_{error}	59.020***	56.870***	62.712***	63.859***
Breusch-Pagan	49.251***	55.636***	60.362***	64.524***
Panel B: Selection Results				
Weight Specification	$W_{S,28}$	$W_{S,23}$	$W_{S,23}$	$W_{S,28}$
Model Specification	SDM	SDM	SDM	SDM
Estimator	GMM/IV	GMM/IV	GMM/IV	GMM/IV

Table 5a. Summary Impacts - %Belief

	%Belief			
	(1)	(2)	(3)	(4)
Panel A: Average Direct Effect				
HealthImpact	0.455***			0.466***
	(0.083)			(0.096)
AssetImpact		0.003**		-0.000
		(0.001)		(0.001)
TMax			0.009**	0.007*
			(0.004)	(0.004)
High2016 × ($TMax \leq 163$)			0.002	0.002
			(0.021)	(0.020)
High2016 × ($163 < TMax \leq 182$)			0.003	0.002
			(0.015)	(0.014)
Low2016 × ($182 < TMax \leq 201$)			-0.056**	-0.033*
			(0.018)	(0.017)
Low2016 × ($201 < TMax$)			-0.042**	-0.038**
			(0.017)	(0.017)
Panel B: Average Indirect Effect				
HealthImpact	4.766***			5.962***
	(1.182)			(2.269)
AssetImpact		0.066**		0.016
		(0.026)		(0.040)
TMax			-0.005	-0.023
			(0.031)	(0.040)
High2016 × ($TMax \leq 163$)			0.020	-0.048
			(0.167)	(0.179)
High2016 × ($163 < TMax \leq 182$)			0.076	0.038
			(0.119)	(0.129)
Low2016 × ($182 < TMax \leq 201$)			-0.425***	-0.386***
			(0.071)	(0.084)
Low2016 × ($201 < TMax$)			-0.079	0.261**
			(0.097)	(0.116)
Controls	Yes	Yes	Yes	Yes
Observations	3,108	3,108	3,108	3,108
Weight Specification	$W_{S,328}$	$W_{S,250}$	$W_{S,274}$	$W_{S,449}$
Model Specification	SDM	SDM	SDM	SDM
Estimator	GMM/IV	GMM/IV	GMM/IV	GMM/IV

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$
Note: Coefficient estimates for these specifications can be found in Table 8a

Table 5b. Summary Impacts - %Risk

	%Risk			
	(1)	(2)	(3)	(4)
Panel A: Average Direct Effect				
HealthImpact	0.653^{***}			0.745^{***}
	(0.109)			(0.241)
AssetImpact		0.006^{**}		-0.000
		(0.002)		(0.004)
TMax			0.006	0.004
			(0.005)	(0.005)
High2016 × $(TMax \leq 163)$			-0.000	0.001
			(0.028)	(0.026)
High2016 × $(163 < TMax \leq 182)$			0.013	0.009
			(0.020)	(0.018)
Low2016 × $(182 < TMax \leq 201)$			-0.021	-0.020
			(0.022)	(0.020)
Low2016 × $(201 < TMax)$			-0.015	-0.009
			(0.018)	(0.016)
Panel B: Average Indirect Effect				
HealthImpact	3.912^{**}			28.812
	(1.876)			(54.113)
AssetImpact		-0.011		-0.350
		(0.085)		(0.694)
TMax			-0.159	-0.171
			(0.485)	(0.398)
High2016 × $(TMax \leq 163)$			-1.166	-1.191
			(2.892)	(2.360)
High2016 × $(163 < TMax \leq 182)$			1.181	0.737
			(3.193)	(2.057)
Low2016 × $(182 < TMax \leq 201)$			-0.244	-0.266
			(1.474)	(1.191)
Low2016 × $(201 < TMax)$			0.896	1.242
			(2.346)	(1.242)
Controls	Yes	Yes	Yes	Yes
Observations	3,108	3,108	3,108	3,108
Weight Specification	$W_{S,28}$	$W_{S,23}$	$W_{S,23}$	$W_{S,28}$
Model Specification	SDM	SDM	SDM	SDM
Estimator	GMM/IV	GMM/IV	GMM/IV	GMM/IV

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$
Note: Coefficient estimates for these specifications can be found in Table 8b

Table 6. Robustness of Summary Impacts to Alternative Spatial Weight Specifications

	%Belief			**%Risk**		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Average Direct Effect						
HealthImpact	0.466***	0.459***	0.463***	0.745***	0.658***	0.607***
	(0.096)	(0.105)	(0.107)	(0.241)	(0.176)	(0.167)
AssetImpact	-0.000	-0.000	-0.000	-0.000	0.000	0.001
	(0.001)	(0.001)	(0.001)	(0.004)	(0.003)	(0.003)
Panel B: Average Indirect Effect						
HealthImpact	5.962***	2.901**	2.000*	28.812	8.584	4.248
	(2.269)	(1.410)	(1.087)	(54.113)	(9.583)	(4.924)
AssetImpact	0.016	0.013	0.008	-0.350	0.093	-0.041
	(0.040)	(0.026)	(0.021)	(0.694)	(0.145)	(0.082)
Weight Selection Criteria	Goodness-of-fit	Moran's I	Parsimony	Goodness-of-fit	Moran's I	Parsimony
Temperature Heuristics	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,108	3,108	3,108	3,108	3,108	3,108
Weight Specification	$W_{S,449}$	$W_{S,137}$	$W_{S,58}$	$W_{S,28}$	$W_{S,18}$	$W_{S,13}$
Model Type	SDM	SDM	SDM	SDM	SDM	SDM
Estimator	GMM/IV	GMM/IV	GMM/IV	GMM/IV	GMM/IV	GMM/IV

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Table 7. Robustness of Summary Impacts to Alternative Horizons of Extreme Weather Impacts

	%Belief			%Risk		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Average Direct Effect						
HealthImpact	0.467***	0.466***	0.613***	0.790*	0.745***	0.922***
	(0.079)	(0.096)	(0.129)	(0.479)	(0.241)	(0.250)
AssetImpact	-0.001	-0.000	-0.001	-0.003	-0.000	-0.001
	(0.001)	(0.001)	(0.002)	(0.006)	(0.004)	(0.004)
Panel B: Average Indirect Effect						
HealthImpact	4.856***	5.962***	7.098***	61.976	28.812	26.030
	(2.387)	(2.269)	(2.385)	(309.101)	(54.113)	(39.187)
AssetImpact	-0.002	0.016	0.028	-0.696	-0.350	-0.326
	(0.034)	(0.040)	(0.049)	(3.363)	(0.694)	(0.553)
Horizon	20	30	40	20	30	40
Temperature Heuristics	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,108	3,108	3,108	3,108	3,108	3,108
Weight Specification	$W_{S,449}$	$W_{S,449}$	$W_{S,449}$	$W_{S,28}$	$W_{S,28}$	$W_{S,23}$
Model Type	SDM	SDM	SDM	SDM	SDM	SDM
Estimator	GMM/IV	GMM/IV	GMM/IV	GMM/IV	GMM/IV	GMM/IV

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

5. Discussion

Climate change is an urgent global challenge that requires coordinated action from individuals, firms, and governments to mitigate future damages. However, substantial variability in climate opinion across US counties threatens to hinder these efforts (Howe et al. (2015)), with widespread climate skepticism and low levels of concern unlikely to contribute to the broad public support needed to catalyze effective climate action (Snow et al. (2008)). This has sparked significant academic interest in the factors that influence climate opinion. Previous studies have yielded strong evidence in support of education (Angrist et al. (2024)), local fossil fuel activity (Dewitte (2023)), gender (Egan and Mullin (2012)), partisanship (Dunlap and McCright (2008), and temperature-based experiential cues (Kaufmann et al. (2017)). By contrast, the role of extreme weather – a vivid and emotionally salient heuristic closely tied to climate change – remains a topic of debate. Despite its strong psychological basis, the literature is in disagreement as to whether extreme weather produces an experiential learning effect on climate beliefs and risk perceptions (Hughes et al. (2020), Konisky et al. (2016), Sloggy et al. (2021), Brulle et al. (2012), Carmichael and Brulle (2017), Lyons et al. (2018)). However, in an extensive review of the literature, Howe et al. (2019) point out that this disagreement may be due to these studies' failure to account for spatial dependence in the climate opinion formation process – an omission that could lead to biased statistical inference (Anselin and Bera (1998)).

This paper helps settle this long-standing debate while also revealing important nuances in the climate opinion formation process that were not addressed by previous studies. We leverage tools from the spatial econometrics literature (LeSage and Pace (2009) to evaluate the relationship between extreme weather and climate opinion at the US county level while accounting for spatial spillovers between socially connected counties. Our results reveal four key insights. First, they demonstrate that residents of counties experiencing more severe extreme weather are more likely to believe that climate change is happening. We refer to this as the direct experiential learning effect of extreme weather on climate belief. Second, by also incorporating the temperature heuristics proposed by Kaufmann et al. (2017) in our econometric specifications, our results indicate that extreme weather events produce direct experiential learning effects on climate beliefs that are two to three times larger in magnitude than those of longer-term changes in temperature. Third, extreme weather distinguishes itself from temperature-based experiential cues in our results by also producing a direct experiential learning effect on climate risk perceptions. And fourth, our results demonstrate that spatial spillovers arise in the formation of climate beliefs, but not risk perceptions.

These insights strengthen our understanding of the mechanisms driving climate opinion and have practical implications for climate communications and disaster preparedness. While increasing public awareness of extreme weather in other regions can enhance climate beliefs, elevating risk perceptions requires direct, local experience with extreme weather. This distinction is particularly relevant as climate change continues to alter the spatial distribution of extreme weather, placing previously low-risk communities at greater future risk. Addressing this challenge will require innovative approaches to climate communications and disaster risk management that anticipate emergent high-risk areas and foster proactive public responses.

5.1. **Gaps & Future Work.** While a large, interdisciplinary body of research on climate opinion has taken shape over the past two decades, numerous gaps remain which would advance this research agenda. First, the literature remains highly US-centric. Data on public perceptions of climate change are more widely available in the United States than any other country, and extensive climate records allow for a wide variety of experiential drivers to be explored at various spatial and temporal scales. However, we echo the calls of previous studies for research in more diverse geographic contexts (Capstick et al. (2015), Borick and Rabe (2017), Howe et al. (2019)). By filling this gap, future research could further validate the findings from US-based studies, while also shedding light on how culture, politics, and other contextual factors shape the climate opinion formation process. Moreover, these studies are increasingly possible as climate opinion polling improves in other countries. For example, spatially-resolved climate opinion estimates are now also available in Canada (Mildenberger et al. (2016)), India (Marlon et al. (2019)), and Ireland (Leiserowitz et al. (2021)).

Second, many important nuances of the climate opinion formation process have yet to be evaluated quantitatively. This paper makes some headway in this regard, identifying important distinctions between extreme weather- and temperature-based experiential cues and their roles in shaping two distinct opinion-based outcomes (beliefs and risk perceptions). However, the literature has almost exclusively focused on population-level effects. In doing so, it has ignored heterogeneities that would be highly relevant to policymakers and climate communicators alike. For example, existing research has highlighted the gulf in climate opinion across political groups (Dunlap and McCright (2008), McCright and Dunlap (2011b), McCright and Dunlap (2011a), Guber (2013)), but has offered relatively little quantitative evidence regarding its causes. Within-group dynamics may partially explain why this gap has widened over time (for example, in line with Moussaïd et al. (2013) and Sunstein et al. (2018)), but spatially-resolved climate opinion estimates by political group within the United States (Mildenberger et al. (2017)) allow new hypotheses to be tested. Meanwhile, existing disaster risk indices such as FEMA's National Risk Index for Natural Hazards (Zuzak et al. (2022)) acknowledge that socially vulnerable communities disproportionately shoulder the effects of natural disasters. However, existing research has yet to explore whether extreme weather differentially affects climate opinion in more socially-vulnerable communities. Studies that quantify heterogeneous effects such as these could play an important role in shaping climate policy and communications efforts in the future.

And third, the climate opinion formation literature would be complemented by quantitative research which establishes a relationship between climate opinion and economic, political, or social outcomes. The relatively limited research in this area has tended to focus on behavioural intentions, such the relationship between environmental awareness and EV purchase intentions (Mustafa et al. (2022)). The importance of studying realized behavioural outcomes, however, is reinforced by evidence of an intention-behaviour gap (Glanz et al. (2015)). For example, He et al. (2023) find evidence of such a gap in households' adoption of energy-saving appliances. A study by Hazlett and Mildenberger (2019) – which links Californian communities' wildfire exposure to support for climate policy – has helped address this gap in the literature, but further contributions would be a welcome addition to the literature and strengthen its external validity.

Appendix A. Extended Literature Review

Over the past century, research in social psychology has significantly advanced our understanding of how attitudes, beliefs, and judgements are formed. Psychological theories offer valuable frameworks for interpreting the processes through which individuals form opinions about complex and contested topics, such as climate change. As Howe et al. (2019) argue, these theories provide a powerful lens through which researchers can approach the growing body of empirical work on climate opinion. By grounding empirical strategies in established psychological frameworks and interpreting results through the lenses of these theories, researchers can gain a more nuanced understanding of the mechanisms that shape climate beliefs and identify new directions for inquiry.

In this section, we aim to bridge the theoretical and empirical domains to establish a firm foundation for this paper. In Section A.1, we introduce a variety of psychological theories and discuss their implications for how individuals process information and form judgements, with a particular focus on dual process theories and the heuristic-systematic model. In Section A.2, we review the empirical literature on the drivers of climate opinion through the lenses of these theories, contextualizing key findings within their theoretical frameworks. Together, these sections demonstrate the dynamic interplay between cognitive processes, motivational factors, and informational cues in shaping climate beliefs.

A.1. **Theory: The Psychology of Opinion Formation.**

A.1.1. *Dual Process Theories and the Heuristic-Systematic Model.* Dual process theories provide a foundational framework for understanding how individuals process information, arguing that they rely on two distinct modes of information processing (Kahneman (2013)). Type 1 processing relies on easily noticed and understood informational cues, such as social norms, authority endorsements, or emotionally salient events. This mode of information processing is cognitively efficient but less thorough, often relying on mental shortcuts. In contrast, type 2 processing involves a deeper, more analytical evaluation of information. Individuals scrutinize the quality, consistency, and relevance of available evidence, often leading to more robust and accurate conclusions, albeit at a greater cognitive and temporal cost. In the heuristic-systematic model (HSM) (Chaiken (1980), Chaiken and Stangor (1987), Chaiken and Ledgerwood (2012)) – a dual process theory specific to the formation of attitudes and judgements – these are referred to as heuristic and systematic modes of information processing.

By layering a number of features on top of the standard dual process framework, the HSM provides a rich and nuanced lens through which researchers can examine how individuals engage with information. These features make the HSM particularly well-suited for exploring opinion formation in contexts involving complex and contested topics, such as climate change.

These features include the central role of motivation, the divergence between heuristic and systematic signals, the principle of effort minimization, and the constraints imposed by individuals' informational, temporal, and cognitive environments.

First, the HSM asserts that individuals engage in information processing in order to arrive at attitudinal judgements which satisfy their motivational objectives. In doing so, it places the nature and strength of one's motivation at the heart of its model of attitude formation. These objectives may be based on a desire to either (i) achieve a desired level of judgemental confidence (termed *accuracy motivation*) or (ii) arrive at a judgement that aligns with self-focused variables such as one's priors (termed *defensive motivation*) or other-focused variables such as the judgements of an influential individual or group (termed *impression motivation*). Because the latter two of these motivations are associated with selective information processing and confirmation bias (Hart et al. (2009)), the nature of one's motivation can lead to differential judgements in and of itself.

Second, in line with other dual process theories, the HSM acknowledges that heuristic and systematic processing may provide different signals regarding a topic of interest. This divergence arises in part due to the susceptibility of heuristic-based reasoning to a wide range of behavioural biases, including anchoring, availability, and representativeness biases (Tversky and Kahneman (1974)). Meanwhile, the more comprehensive, analytical evaluation of evidence that takes place during systematic processing reduces the likelihood of biased conclusions (although Chaiken and Ledgerwood (2012) note that it does not eliminate them entirely). Different modes of information processing can therefore lead to different – and at times coflicting – conclusions being drawn, even from the same underlying information set.

Third, the principle of effort minimization underscores the dynamic interplay between cognitive effort and motivational goals within the HSM, with individuals striving to achieve their motivational objectives with the least cognitive effort. Heuristic processing, being less demanding, can therefore be understood as the default mode of information processing, with individuals only engaging in systematic processing when heuristic cues are insufficient to satisfy their motivational objectives. This could occur when an individual's accuracy motivation is strong or when heuristic signals are ambiguous or contradictory. In light of evidence that climate change is secondary to other daily concerns (Marx et al. (2007), Weber and Stern (2011)), heuristic processing may therefore be particularly prevalent in the formation of climate opinion.

And fourth, individuals' capacity to engage in systematic processing is constrained by both internal factors, such as their inherent cognitive ability, and external factors, such as the composition of their information set and the amount of time they can devote to the judgement. For instance, individuals with limited access to reliable information or facing significant time pressures may rely on heuristic processing, even when systematic processing would otherwise be preferable. These constraints emphasize the importance of context in shaping how individuals process information and form attitudes.

A.1.2. *Complementary Psychological Theories and the Sources of Informational Cues.* While the heuristic-systematic model is relatively comprehensive, it remains agnostic about the nature of evidence in an individual's information set. Alternative theories of learning take a narrower approach with respect to sources of these informational cues, with two theories highlighting the importance of experiential and social cues in the opinion formation process.

Experiential learning theory (Kolb (1984)) posits that learning is a dynamic, cyclical process where individuals relate concrete experiences and observations to abstract conceptualizations. This process enables individuals to test their existing beliefs while simultaneously forming new ones, with experiential cues serving as vivid and emotionally salient anchors for learning. In the context of climate opinion formation, extreme weather events represent particularly vivid experiential cues. These events are emotionally impactful and easily retrieved from memory, making them powerful drivers of belief formation. Kolb further emphasizes the centrality of individuals' interactions – both physical and cognitive – with their environment, suggesting that people's experiences with their local climate are unavoidable and thus a feasible mechanism for shaping climate beliefs. Given the link between personal experience and belief implied by this theory, the salience of extreme weather provides a compelling rationale for evaluating the role of extreme weather in shaping climate opinion.

By contrast, social learning theory (Bandura (1977)) assigns a central role to observations of others in the learning process, emphasizing that individuals form and revise beliefs not only through personal experience but also by observing the experiences and attitudes of others. In the context of climate opinion formation, this implies that beliefs about climate change are shaped not just by an individual's direct interactions with local climatic conditions, but also by the beliefs and experiences of others within their social network. Social learning therefore reinforces the potential for spatial dependence in climate opinion, as individuals are often influenced by those geographically or socially proximate to them. Experimental evidence by Moussaïd et al. (2013) supports this notion, finding that individuals revise their judgements after exposure to others' opinions and confidence levels. This interaction can create two distinct attractors of opinion: the expert effect, where individuals gravitate toward the views of perceived experts, and the majority effect, where they conform to dominant group norms. These dynamics highlight the importance of social spillovers in shaping climate beliefs, particularly in spatially interconnected settings. We discuss the implications of these social dynamics for statistical inference and our empirical strategy in Section 3.

Together, these theories suggest that experiential and social cues are critical to understanding how individuals form and update their attitudes toward climate change. While the HSM provides a robust framework for analyzing the cognitive and motivational dimensions of opinion formation, the theories of Kolb (1984) and Bandura (1977) complement it by highlighting the role of external, context-specific informational cues that may amplify or mediate the processes described by the HSM.

A.2. **Empirical Evidence on the Drivers of Climate Opinion.**

A.2.1. *The Role of Experiential Learning.* According to Kolb's experiential learning theory (Kolb (1984)), concrete experiences are an important mechanism by which individuals form their attitudes and beliefs. Weather – a tangible, daily phenomenon that everybody is exposed to – therefore provides direct signals that can inform individuals' beliefs and risk perceptions regarding climate change. These weather-based experiences are also natural candidates for heuristic-based processing. Extreme weather events and temperature anomalies are vivid, emotionally salient, and conceptually aligned with climate change, making them easily retrieved from memory and particularly influential in shaping climate opinion. Moreover, because climate change often takes a backseat to more immediate daily concerns and engaging with complex scientific evidence is cognitively challenging (Marx et al. (2007), Weber and Stern (2011)), these experiential, heuristic-based cues may play an outsized role in shaping climate opinion. By offering accessible and relatable signals, weather-based experiences enable individuals to form judgements about climate risks without the need for extensive analytical engagement.

Temperature, perhaps reflective of its conceptual alignment with the notion of a warming planet, has received considerable attention in the literature on climate opinion. A statistically significant relationship between short-term temperature anomalies and enhanced climate change beliefs and concerns has been observed repeatedly across studies, including Joireman et al. (2010) Li et al. (2011), Hamilton and Stampone (2013), Brooks et al. (2014), Zaval et al. (2014), Bohr (2017), and Lee et al. (2018). For example, Brooks et al. (2014) find that quadratic deviations from the long-term mean temperature occurring on the date of the survey are associated with elevated risk perceptions. Studies of longer-term temperature trends have been less conclusive, with a large number of studies both supporting (Shao et al. (2014), Shao et al. (2016), Shao (2017), Deryugina (2013), Donner and McDaniels (2013), Borick and Rabe (2014), Zahran et al. (2006), Hamilton and Keim (2009)) and refuting (Brulle et al. (2012), Carmichael and Brulle (2017), Marlon et al. (2019), Shum (2012), Brody et al. (2008)) effects based on longitudinal changes in temperature. Perhaps the strongest example in this literature, however, comes from Kaufmann et al. (2017). They introduce a novel measure of local changes in climate based on the relative timing of record high and low temperatures over multiple decades, and supplement it with measures of short-term warm and cold temperature anomalies[8]. Their results suggest that long-term warming

[8] Additional information on the temperature heuristics constructed by Kaufmann et al. (2017) can be found in Section 2.3.

increases beliefs in climate change at the US county level, but that this effect is dampened by recent cold anomalies which reduce beliefs. Another strength of their contribution lies in their empirical strategy. Recognizing the potential for spatial dependence in this setting and the empirical challenges it would introduce (Anselin and Bera (1998), Anselin (2022)), they adopt techniques from the spatial econometrics literature to mitigate the risk of statistical bias. Crucially, this risk may help explain the conflicting conclusions of earlier studies.

Compared to temperature-based cues, the relationship between extreme weather and climate opinion has received relatively less attention in the literature, and the results are far from conclusive. While several studies have found evidence that extreme weather influences climate opinion, the observed effects tend to be small (Konisky et al. (2016), Hughes et al. (2020), Sloggy et al. (2021). For example, Hughes et al. (2020) find some evidence that drought and precipitation anomalies are associated with enhanced climate change beliefs and risk perceptions in Australia, but note that the results do not extend to temperature anomalies. Conversely, other studies have failed to identify a statistically significant relationship, including Brulle et al. (2012), Cutler (2016), Carmichael and Brulle (2017), and Lyons et al. (2018). Meanwhile, there is also some disagreement in the literature regarding the persistence of these effects. In one of the few studies that exploits longitudinal data, Konisky et al. (2016) find evidence that exposure to extreme weather increases American residents' concern about climate change, but only for recent events. In contrast, Sloggy et al. (2021) find that both recent and past hurricanes are associated with enhanced beliefs in climate change, suggesting that some effects may endure over time.

The small effect sizes and general disagreement in the literature is somewhat surprising in light of the theoretical framework established earlier. Extreme weather events are conceptually salient to climate change, as they are widely associated with the consequences of a warming planet. Moreover, extreme weather can result in significant disruptions to individuals' livelihoods, with some effects – such as property damage, adverse health outcomes, or loss of income – having long-term consequences. Even when these impacts are short-lived, the vivid and emotionally salient nature of extreme weather events makes them easily retrieved from memory, enhancing their capacity to shape climate opinion through heuristic-based processing. Given these factors, one might expect extreme weather to exert a stronger and more persistent influence on climate beliefs than the literature currently suggests.

This study addresses these gaps by incorporating spatial econometric techniques that explicitly account for spatial dependence. This approach – which reduces the risk of statistical biases and allows us to capture the full range of extreme weather's effects, including both direct impacts on affected counties and indirect impacts on other geographically or socially proximate counties – has been advocated for by Howe et al. (2019) in a comprehensive review of the literature, but has not been incorporated into more recent studies of extreme weather and climate opinion. By responding to the call to action of Howe et al. (2019), this paper aims to mirror the contributions of Kaufmann et al. (2017) in this adjacent literature.

A.2.2. *The Role of Education.* Educational attainment plays a crucial role in the opinion formation process, operating through two distinct channels. First, education can be viewed as an accumulation of human capital that increases an individual's ability to engage in systematic processing. Because heuristic and systematic modes of information processing can lead to different conclusions from the same information set, this lessening of cognitive constraints may independently influence judgements. This mechanism is particularly relevant in the domain of climate change, with Weber and Stern (2011) demonstrating that a large portion of the general population have difficulty understanding scientific evidence about climate change. Alternatively, educational attainment can be viewed as expanding an individual's information set. In the context of this study, education may influence an individual's opinions about climate change by exposing them to a broader array of scientific and environmental knowledge, which could shift their beliefs and risk perceptions.

Empirically, a robust relationship has been established between educational attainment and climate opinion. By exploiting new compulsory school laws in 16 European countries, Angrist et al. (2024) were able to estimate the causal effects of educational attainment on a variety of pro-environmental outcomes, including beliefs in climate change. Their instrumental variables estimates suggest that an additional year of education results in a 4.0 percentage point increase in an individual's probability of holding pro-environmental beliefs. Hamilton et al. (2015) complement this work by finding that education dominates other socioeconomic factors in predicting climate opinion, but also that the effects are moderated by political orientation. In light of this strong and robust relationship, educational attainment has been exploited as an individual-level predictor in the construction of spatially resolved climate opinion estimates in the United States (Howe et al. (2015)), Canada (Mildenberger et al. (2016)), and Ireland (Leiserowitz et al. (2021)).

A.2.3. *The Role of Local Industry.* The multi-motive interpretation of the HSM provides an intuitive framework for understanding how local industry influences climate opinion, operating through a sequential process involving both defensive and impression motivations.

First, defensive motivation seeds skepticism about climate change among individuals whose personal or economic interests are directly threatened by it. In fossil fuel-dependent communities, individuals working in the industry may perceive that acknowledging the need for a transition to renewable energy endangers their livelihoods, careers, and local economies. This perceived threat can lead individuals to process information in a way that defends their pre-existing attitudes, either by scrutinizing evidence selectively or by relying on heuristic cues that justify climate skepticism, such as dismissive narratives about human-caused climate change.

Second, impression motivation facilitates the diffusion of these doubts throughout communities. Living in a fossil fuel-dependent community exposes individuals to influential leaders, peers, and organizations that may actively espouse climate-skeptical attitudes as part of a defensive strategy. These influential figures shape local norms, creating a social environment where aligning with skeptical attitudes becomes a way to gain acceptance or maintain cohesion within the group. Impression motivation drives individuals to adopt these attitudes, not necessarily because they align with their personal beliefs, but because they seek to align with the expectations of their peers, employers, or community leaders. As such, defensive motivations seed doubt, while impression motivations help those doubts spread, reinforcing a climate-skeptical culture.

Empirically, Dewitte (2023) makes a compelling case that climate skepticism in the United States can be explained by communities' historical exposure to extractive industries. To do so, this study first develops a novel dataset of 3.6 million oil and gas wells drilled between 1859 and 2022 and uses it to measure a county's historical exposure to fossil fuel extraction as the number of decades during which at least one oil and gas producing well was drilled. Dewitte then estimates the relationship between this measure and climate opinion, finding that an additional decade of exposure in an individual's county of residence decreases the probability that they believe in climate change by 0.15-0.20 percentage points. Dewitte further supports this finding by demonstrating that historical exposure is associated with the development of local "oil identities." Dewitte does so by identifying a causal link between historical industry activity and the naming of local sports teams (such as the "Oilers"). Local industry characteristics have also been incorporated as individual-level predictors in the construction of spatially resolved climate opinion estimates in the United States (Howe et al. (2015)) and Canada (Mildenberger et al. (2016)), further reinforcing their role in shaping climate beliefs and risk perceptions.

A.2.4. *The Role of Gender.* Gender differences in climate opinion have been established across a large number studies, consistently showing that women exhibit higher levels of climate belief and concern than men do (O'Connor et al. (1999), Brody et al. (2008), McCright (2010), McCright and Dunlap (2011b), Egan and Mullin (2012)). For example, McCright (2010) finds that women are more likely to worry about global warming than men (35% to 29%), to believe that it will threaten their way of life (37% to 28%), and to believe that it is underestimated by the media (35% to 28%). These observations are most commonly attributed to gender difference in risk preferences. Women are consistently found to be more risk averse than men (Slovic (1999), Sarin and Wieland (2016)) and may therefore perceive climate change as a greater threat. Within the HSM, this heightened perception of risk could strengthen their accuracy motivation, increasing their propensity to process climate-related information in a systematic manner and, ultimately, guide adaptive planning. By contrast, lower levels of risk aversion in men may weaken their accuracy motivation, leading them to rely on heuristic processing which is more susceptible to errors in judgement and behavioural biases (Tversky and Kahneman (1974)).

Although is it often overlooked in the literature, gender differences in confidence can also help explain these empirical results. Despite evidence that women possess more accurate climate-related knowledge than men, women are more likely to underestimate their knowledge than men are (McCright (2010)). This underestimation heightens perceptions amongst women that heuristic cues are insufficient to achieve their desired level of accuracy, thus increasing their propensity to engage in systematic processing. By contrast, men, exhibiting overconfidence in their knowledge, may rely more heavily on heuristic-based cues, even when such cues may lack sufficient informational depth. This divergence in confidence levels can therefore result in systematic differences in the propensity to scrutinize climate-related information between men and women, ultimately leading to a divergence in climate opinion between the two groups.

A.2.5. *The Role of Political Affiliation and Ideology.* Across a wide range of studies, the political party one supports has been identified as a strong predictor of climate opinion (Dunlap and McCright (2008), McCright and Dunlap (2011a), McCright and Dunlap (2011b), Guber (2013), Mildenberger et al. (2017)). Similar to local fossil fuel industry exposure, political affiliation's role in shaping public perceptions of climate change can be understood through the interaction of defensive and impression motivations. Political leaders represent an influential reference point which party supporters may be motivated to align with. Once a certain attitudinal view takes hold within a political group, impression motivations are strengthened by the additional draw of aligning with the majority of one's peers. And for those who have updated their judgements in align with their party stance, their stance can become entrenched by a propensity to defend your priors (defensive motivation). However, while an association between partisanship and climate opinion has been established across a myriad of studies, uncertainty remains regarding the predominant direction of causality in this relationship. While partisanship may vary well shape one's opinions about climate change, the party one supports may very well also be shaped by one's perceptions of important policy issues.

A.2.6. *The Role of Spatial Spillovers.* Spatial spillovers can arise in the climate opinion formation process for a variety of reasons. First and foremost, both psychological theories (Bandura (1977)) and experimental evidence (Moussaïd et al. (2013)) support the notion that individuals are social learners, forming their judgements in part based on their exposure to the opinions and perspectives of others. Second, individuals are increasingly exposed to out-of-county informational cues due to the simultaneous decline in local news outlets and rise of media conglomerates and digital platforms (Ardia et al. (2020)). And third, due to the significant amount of inter-county migration in the United States (Ambinakudige and

Parisi (2017)), many county residents' exposure to experiential cues – such as local changes in temperature or extreme weather – will have been shaped by experiences in multiple locations.

Unfortunately, the literature on climate opinion formation has largely ignored these effects. This is a critical shortcoming not only because of the richness that identifying and quantifying spatial spillovers brings to the topic, but also because of the challenges it introduces for statistical inference. This latter point is emphasize by Howe et al. (2019), who suggest that disagreements in the literature regarding the influence of experiential, weather-based cues in this setting may be partially attributable to spatial autocorrelation in the error term and bias that this may introduce to coefficient estimates (Anselin and Bera (1998)). Kaufmann et al. (2017) break this mold, accounting for spatial spillovers in their study of how local changes in temperature influence climate opinion through the inclusion of a spatially lagged dependent variable. In a similar vein, one of the primary contributions of this paper is to estimate spatial spillovers in the climate opinion formation process related to a phenomenon with extensive news coverage: extreme weather.

A.2.7. *The Role of Asymmetric Behavioural Biases.* Viewed differently, Sunstein et al. (2018) argue that polarization in climate change perceptions can arise in response to asymmetries in how climate believers and skeptics update their judgements in response to new information. In an experimental setting, participants with skeptical priors were observed to become more skeptical in response to unexpected positive informational cues (for example, that temperatures are expected to rise less than previously anticipated) and not update their position at all in response to unexpected negative informational cues (for example, that temperatures are expected to rise more than previously anticipated). Participants with more pro-environmental priors exhibited the exact opposite response, believing more strongly in climate change in response to unexpected negative news and not updating their beliefs at all in response to unexpected positive news. This view is further supported by Howe and Leiserowitz (2013), who explore whether individuals' perceptions of how their local climate has changed are primed by their prior beliefs regarding whether climate change is happening. They find evidence that those who are skeptical of climate change are more likely to underestimate the amount by which their local climate has warmed.

Within the HSM, these observations can be understood through the lens of defensive motivation. Individuals are at times motivated to defend their prior beliefs and, in doing so, exhibit a higher propensity to engage in selective information processing. For example, Hart et al. (2009) find that individuals are nearly two times more likely to select information which supports their priors than information which refutes it when called to update their judgements. This evidence emphasizes the importance of studying public perceptions in dynamic contexts, although researchers have largely been constrained in this regard due to a lack of longitudinal datasets on climate opinion.

Appendix B. Supplementary Technical Information

B.1. **Estimating Climate Opinion: Yale Program for Climate Communications Methodology (Howe et al., 2015).** In their US Climate Opinion Maps, Howe et al. (2015) provide the first and only spatially resolved estimates of climate change beliefs, risk perceptions, and policy preferences in the United States. These estimates are made possible through advances in a survey down-scaling technique known as multi-level regression and post-stratification (MRP). At the foundation of this approach are several waves of a probability-based, regionally stratified, and nationally representative survey ($n > 28,000$). During the multi-level regression step, these survey responses are used to estimate the following linear probability model, relating stated beliefs to individual- and geography-level covariates in the survey sample:

$$Opinion_{jc} = \alpha_c + \sum_{k=1}^{q} \beta_k R_{kj} + \eta_{jc} \tag{15}$$

where $Opinion_{jc}$ is the coded response to either of the questions posed above for respondent j in county c, R_{jk} is an individual-level regressor for respondent j, β_k is the regression coefficient on R_{jk}, η_j is an error term, and α_c captures both observed and unobserved county-level variation. Then in the post-stratification step, county-level climate opinion estimates are produced by relating these coefficient estimates to known features of the US population. To do so, the authors first segment the US population into strata s defined by permutations of realized values of these individual- and county-level regressors in the full US population. They then calculate fitted values for each strata (denoted $\widehat{Opinion}_s$) based on equation (15), and estimate climate opinion in county c (denoted $\%Opinion_c$) as the population-weighted average of the strata estimates $\widehat{Opinion}_s$ within county c:

$$\%Opinion_c = \frac{\sum_{s \in c} N_s \widehat{Opinion}_s}{\sum_{s \in c} N_s} \tag{16}$$

where N_s is a count of the adult population in strata s. This approach has been thoroughly validated by public opinion scholars (Park et al. (2006), Lax and Phillips (2009), Warshaw and Rodden (2012), Buttice and Highton (2013)).

B.2. **Assignment of Temperature Heuristic Observations from Weather Stations to US Counties.** As noted in Section 2.3, the heuristics for local changes in temperature reconstructed from Kaufmann et al. (2017) are first constructed for 4,924 weather stations located in the United States. Station-level heuristic values are then assigned to US counties within QGIS, a geographic information system software, by the following method. First, we construct Thiessen polygons using the point coordinates of weather stations as an input. Thiessen polygons are used to allocate planar space to points in space by defining an area around a point where every coordinate is nearer to this point than any other. This step is depicted in Figure 5, with the weather stations depicted by yellow points and the Thiessen polygons by white lines. Next, we perform a spatial join between the Thiessen polygons and the county boundaries (depicted by the black lines) to form a larger sample of smaller polygons. We will call these 'joined polygons'. Each joined polygon is associated with exactly one county and one station-level index value. Finally, a county-level heuristic value $Heuristic_c$ is calculated for each county by taking the landmass-weighted average of the joined polygons within it:

$$Heuristic_c = \frac{\sum_{j \in s} Landmass_j \times TMax_j}{Landmass_c} \tag{17}$$

where $Heuristic_c$ is one of $TMax_c$, $High2016_c$, or $Low2016_c$, $Landmass_j$ is the area of joined polygon j, $Landmass_c$ is the landmass of county c, $TMax_j$ is the index value associated with joined polygon j, and the summation is over joined polygons j within county c.

B.3. **Coefficient Interpretation in Spatial Econometrics.** In Section 3, we note that coefficient interpretation in specifications that contain a spatially lagged dependent variable ($\rho \neq 0$) is complicated by the expansion of the information set to include neighbour effects. As a result of these effects, the partial derivative of y with respect to x_k in this setting is

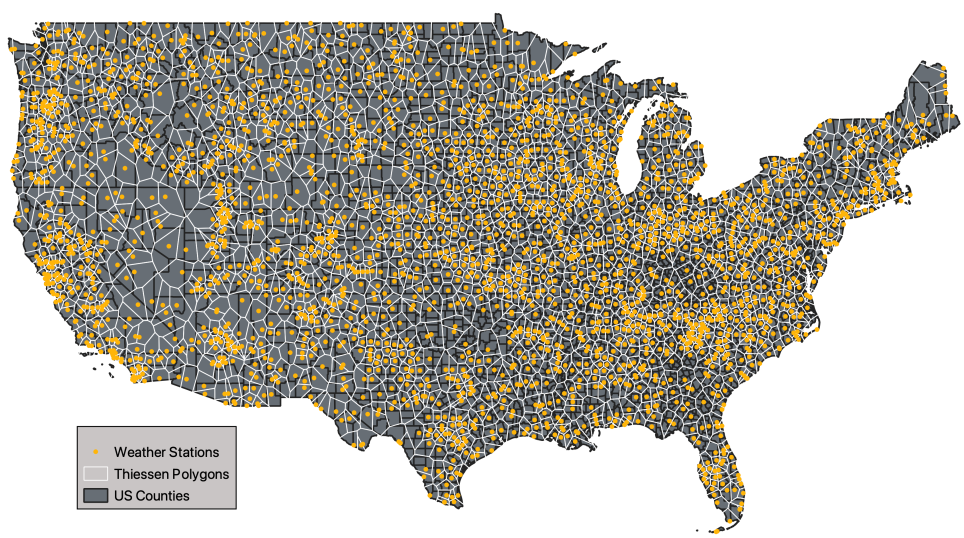

Figure 5. Weather stations, their associated Thiessen polygons, and their intersection with US counties.

no longer equal to the scalar $\hat{\beta}_k$. Instead, it is an $n \times n$ matrix that is a function of the coefficient estimates $\hat{\rho}$, $\hat{\beta}_k$, $\hat{\theta}_k$, and the spatial weight matrix W. To see why, consider the Spatial Durbin specification:

$$y = \rho W y + X\beta + W X\theta + u \tag{18}$$

By the spatially lagged dependent variable to the left hand side, equation (18) can be rewritten as follows:

$$(I - \rho W)y = X\beta + W X\theta + u \tag{19}$$

Isolating y on the left hand side then yields the following expression:

$$y = \sum_{r=1}^{k} S_r(W)x_r + V(W)u \tag{20}$$

where $S_k(W) = V(W)(I\beta_k + W\theta_k)$ and $V(W) = (I - \rho W)^{-1}$. It is then clear from this expression that the partial derivative of y with respect to x_k is equal to the more complicated expression $S_k(W)$.

B.4. **Supplementary Results.** As noted in Section 3, interpreting estimates in specifications with spatially lagged dependent variables are more complex, with coefficient estimates not coinciding with the partial derivative of y with respect to the independent variables X. To address this, we report the summary impact measures proposed by Pace and LeSage (2006) in Section 4. For completeness, we have included the coefficient estimates as supplementary tables.

Table 8a. Coefficient Estimates for Spatial Econometric Specifications - %Belief

	%Belief			
	(1)	(2)	(3)	(4)
Intercept	20.999***	19.756***	14.876***	14.418***
	(2.297)	(2.209)	(2.412)	(2.448)
HealthImpact	0.359***			0.358***
	(0.039)			(0.097)
AssetImpact		0.002		-0.001
		(0.002)		(0.001)
TMax			0.009**	0.008*
			(0.004)	(0.004)
High2016 × ($TMax \leq 163$)			0.001	0.003
			(0.021)	(0.021)
High2016 × ($163 < TMax \leq 182$)			0.001	0.001
			(0.015)	(0.014)
Low2016 × ($182 < TMax \leq 201$)			-0.027	-0.027
			(0.017)	(0.017)
Low2016 × ($201 < TMax$)			-0.044**	-0.042**
			(0.017)	(0.017)
lag.%Belief (ρ)	0.594***	0.615***	0.694***	0.715***
	(0.038)	(0.036)	(0.034)	(0.035)
lag.HealthImpact	1.762***			1.472**
	(0.510)			(0.594)
lag.AssetImpact		0.025**		0.005
		(0.011)		(0.012)
lag.TMax			-0.008	-0.012
			(0.011)	(0.011)
lag.(High2016 × ($TMax \leq 163$))			0.006	-0.016
			(0.055)	(0.056)
lag.(High2016 × ($163 < TMax \leq 182$))			0.023	0.011
			(0.038)	(0.039)
lag.(Low2016 × ($182 < TMax \leq 201$))			-0.115**	-0.093**
			(0.045)	(0.046)
lag.(Low2016 × ($201 < TMax$))			0.070**	0.106***
			(0.034)	(0.035)
Controls	Yes	Yes	Yes	Yes
Observations	3,108	3,108	3,108	3,108
Weight Specification	$W_{S,328}$	$W_{S,250}$	$W_{S,274}$	$W_{S,449}$
Model Specification	SDM	SDM	SDM	SDM
Estimator	GMM/IV	GMM/IV	GMM/IV	GMM/IV

Note 1: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Note 2: Summary impact measures (Pace and LeSage (2006)) are reported in Table 5a.

Table 8b. Coefficient Estimates for Spatial Econometric Specifications - %Risk

	%Risk			
	(1)	(2)	(3)	(4)
Intercept	4.886	1.046	-0.519	-0.202
	(3.014)	(2.575)	(1.844)	(1.841)
HealthImpact	0.527***			0.495***
	(0.097)			(0.096)
AssetImpact		0.006***		0.002
		(0.002)		(0.001)
TMax			0.007**	0.005*
			(0.004)	(0.004)
High2016 × $(TMax \leq 163)$			0.010	0.012
			(0.018)	(0.018)
High2016 × $(163 < TMax \leq 182)$			0.003	0.003
			(0.012)	(0.012)
Low2016 × $(182 < TMax \leq 201)$			-0.019	-0.017
			(0.014)	(0.013)
Low2016 × $(201 < TMax)$			-0.023	-0.020
			(0.013)	(0.013)
lag.%Belief (ρ)	0.839***	0.938***	0.986***	0.984***
	(0.079)	(0.067)	(0.047)	(0.044)
lag.HealthImpact	0.210			-0.010
	(0.331)			(0.313)
lag.AssetImpact		-0.007		-0.008
		(0.006)		(0.006)
lag.TMax			-0.009	-0.008
			(0.07)	(0.007)
lag.(High2016 × $(TMax \leq 163)$)			-0.025	-0.031
			(0.036)	(0.037)
lag.(High2016 × $(163 < TMax \leq 182)$)			0.014	0.009
			(0.024)	(0.025)
lag.(Low2016 × $(182 < TMax \leq 201)$)			0.016	0.013
			(0.028)	(0.029)
lag.(Low2016 × $(201 < TMax)$)			0.035	0.040*
			(0.022)	(0.022)
Controls	Yes	Yes	Yes	Yes
Observations	3,108	3,108	3,108	3,108
Weight Specification	$W_{S,28}$	$W_{S,23}$	$W_{S,23}$	$W_{S,28}$
Model Specification	SDM	SDM	SDM	SDM
Estimator	GMM/IV	GMM/IV	GMM/IV	GMM/IV

Note 1: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$
Note 2: Summary impact measures (Pace and LeSage (2006)) are reported in Table 5b.

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