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# Weather, Salience of Climate Change and Congressional Voting

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## The Harvard Environmental Economics Program

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# Weather, Salience of Climate Change and Congressional Voting

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**Abstract**

Climate change is a complex long-run phenomenon. The speed and severity with which it is occurring is difficult to observe, complicating the formation of beliefs for individuals. We use Google Insights search intensity data as a proxy for the salience of climate change and examine how search patterns vary with unusual local weather. We find that searches for "climate change" and "global warming" increase with extreme temperatures and unusual lack of snow. The responsiveness to weather shocks is greater in states that are more reliant on climate-sensitive industries and that elect more environmentally-favorable congressional delegations. Furthermore, we demonstrate that effects of abnormal weather extend beyond search behavior to observable action on environmental issues. We examine the voting records of members of the U.S. Congress from 2004 to 2011 and find that members are more likely to take a pro-environment stance on votes when their home-state experiences unusual weather.

**Keywords:** Climate Change, Congressional Voting, Weather

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# 1 Introduction

Anthropogenic climate change is one of the most difficult policy problems that humanity faces today. The costs and benefits of mitigating carbon emissions are highly uncertain. The relevant pollutants are globally mixing, which creates an enormous collective action problem. Finally, the process of climate change unfolds over several decades. Because the impacts of climate change manifest themselves as gradual changes in the distribution of weather outcomes, it can be difficult for individuals to observe whether climate change is occurring. In addition, climate change is a one-time event, and individuals cannot possibly draw on prior experience to guide their perceptions. However, public support and understanding are vital to the successful creation and implementation of climate change mitigation and adaptation policies.

A natural proxy for understanding climate change is a short-run weather event. Indeed, Hansen, Sato and Ruedy (2012) describe the effect of climate change as changing the weights on a pair of dice that determine short-run realizations of weather. We estimate the effect of unusually extreme weather conditions on salience of climate change. We proxy for salience using a search intensity index created by Google for the terms "climate change" and "global warming". We control for a wide variety of fixed effects to account for spurious geographic and seasonal relationships and broad temporal trends. Our results are remarkably robust and suggest that short-run weather phenomena do in fact affect the extent to which people think about climate change.

Furthermore, we demonstrate that the effects of weather extend beyond search behavior to the voting records of U.S. Congressional members. Examining *within-member* variation in support for 215 environmental votes tracked by the League of Conservation Voters between 2004 and 2011, we find evidence that voting on environmental issues is correlated with recent extreme weather in a representative's home state. Reassuringly, the correlation between weather and voting does not extend to votes unrelated to the environment. Although the effect is modest in size, our results suggest that that search intensity may provide a useful proxy for voter and legislator concerns and demonstrates an important link between unusual weather and important action on environmental policy.

Our work relates to several other papers. A series of papers attempt to estimate the extent to which individuals respond to short-run weather in forming their beliefs about climate change. Deryugina (forthcoming) uses an annual Gallup poll to determine whether individuals respond to weather fluctuations by Bayesian updating their expectations about climate change. She finds that while short-term weather fluctuations do not affect individuals' beliefs, longer spells of unusually warm weather do have an impact. She also examines heterogeneity by political affiliation and finds that the effect is confined largely to conservative respondents. Hamilton and Stampone (forthcoming) analyze a series of polls of New Hampshire residents. Interestingly, they find that political independents are the only subgroup that respond to recent weather cues in forming their opinions regarding climate change. Owen, Conover, Videras and Wu (2012) find that respondents to a pair of surveys in August 2009 and October 2007 are more likely to support environmentally-protective policy if their state experienced a heat wave or drought during the most recent summer. They also find that people who regularly access more sources of news information are less responsive to weather cues. Egan and Mullin (2012) also find evidence of a response.

A separate literature demonstrates the value of internet search data in modeling economic behavior. Choi and Varian (2009) demonstrate that Google Insights data can be used to predict demand for automobiles, retail sales, home sales, and travel behavior. After several papers demonstrated the efficacy of using Google searches to predict flu outbreaks, Google itself established the Google Flu Trends tool.[1]. Most relevant to our analysis is Kahn and Kotchen (2010). They find that when a state's unemployment rate increases, Google search activity for "global warming" decreases and search activity for "unemployment" increases. That is, concerns about economic conditions "crowd out" attention to the issue of climate change. Our paper approaches the climate attention problem from the opposite direction. Instead of measuring factors that decrease the relative importance of climate change, we examine the extent to which weather signals *increase* its salience. Our analysis suggests a revealed preference approach to determine how weather affects the allocation of limited attention.

Our paper makes two contributions. Previous studies of climate beliefs and weather use surveys waves that are either infrequent or limited to a specific geographic location. In contrast, search intensity is reported weekly for each state – higher frequency reporting provides us much more identifying variation with which to estimate the relationship between weather and search intensity flexibly and to better control for unobserved heterogeneity that might be correlated with both weather and search activity.

Our empirical results suggest this flexibility is important in several dimensions. First, the variation in the data allows us to simultaneously estimate the effects of temperature, precipitation and snowfall. For instance, given a response to an unusually warm winter, we can estimate the relative contributions of warmer-than-average temperatures separately from the effect of a

[1] http://www.google.org/flutrends

lack of snow. Second, we find evidence that the search intensity responds asymmetrically to temperature and snowfall. Third, the effects of weather on search intensity vary by season. For instance, in the winter, unusually cold and warm weather are both correlated with increased search. Finally, we find that the effect of weather varies substantially by state characteristics. In particular, we find evidence that the response to weather is correlated with a state's economic exposure to weather dependent industries. For example, the response of states for which agriculture (or winter tourism) represents a large share of the economy is different than states with little agriculture (or less winter tourism). We provide the first evidence that states with climate-sensitive economies respond more to weather cues than states without such concerns and that the response is more strongly correlated with weather shocks that affect the local economy.

Our second contribution to is to provide an important link between weather and search behavior to observable actions related to the environment – specifically, the voting behavior of members of the U.S. Congress on environmental issues. Previous work has focused on individual attitudes as the explanatory variable of interest, but has not established a link between weather and tangible changes in behavior. Our work fills an important gap in this sense. Controlling for member fixed effects, we find that U.S. congressional members are more likely to take a pro-environment stance on issues and votes when their home state experiences unusual weather and search intensity in their home-state is high. Reassuringly, the effects are specific to environmental legislation – we do not find similar effects of weather or search intensity on non-environmental legislation. Although the effects we estimate are modest in size (as would be expected) and may not affect the ultimate outcome of the vote, our results suggest that extreme local weather is one of many factors that legislators may consider when voting on environmental issues. Furthermore, our results suggest that search intensity may provide a useful proxy for the salience of issues to voters.

Our paper proceeds as follows. Section 2 describes the data and econometric approach. Section 3 presents the empirical results related to weather and search intensity. Section 4 explores possible heterogeneity in the results based on economic factors and political affiliation. Finally, Section 5 examines the relationship between extreme weather, individual search behavior and voting of members of Congress on environmental issues. In the Appendix, we demonstrate the robustness of our results to a number of different specifications.

# 2 Methodology

## 2.1 Data

**Search intensity data** Our proxy for climate change salience uses the Google Insights search index. This tool is outlined in Stephens-Davidowitz (2011). Essentially, Google Insights tracks the relative frequency with which a given search term is used. In most of our specifications, we use the index for searches of ("global warming"+"climate change") at the state-week level. The index is constructed to allow for accurate comparisons across periods and locations; that is, a given search term is scaled by the overall level of search activity in each state. The advantage of this approach is that a populous state, such as California, will not have a mechanically higher search index than a less populous state, such as Iowa. Thus, our measure of the search term corresponds to search intensity, conditional on overall search activity. Google censors search terms that do not surpass a certain threshold in terms of *absolute* search volume. This affects approximately 20% of our sample from 2004-2011, but is most relevant in 2004-2006 for sparsely populated states in the upper Midwest and Rocky Mountain region. In the appendix, we re-run our regressions using only state-years for which complete data is available and find that our results do not change substantively.

**Weather data** Our weather data comes from the National Climatic Data Center (NCDC). The NCDC collects daily weather station data for over 10,000 U.S. weather stations. The typical station records minimum and maximum daily temperature, precipitation and in some cases, snowfall, snow depth and other meteorologic variables. For purposes of this paper, we limit our analysis to 6,624 stations with data on minimum and maximum temperatures from 2004 to 2011. The stations are located through the 50 states − Rhode Island has the fewest stations (8) and California, the most (370). For each daily station record, we calculate the deviation of maximum daily temperature, precipitation, snowfall and snow depth from a 10-year baseline from 1994 to 2003 and matched by day of the year. To match the search intensity data, we aggregate up to the state-week level.

**Summary Statistics** To illustrate one dimension of our weather variation, we plot monthly average temperature deviations from the 1994-2003 baseline in Figure 1 going back to 1974. The red line is the lagged 12-month moving average deviation. The green line is a linear trend and illustrates that temperatures have been increasing on average since 1974. The linear trend is less pronounced if we focus solely on the last two decades (Figure 2). Although average temperatures have risen since 1974, the warmest 12-month period in U.S. history prior to 2012 stretched from late-1999 to late-2000, during the 10-year baseline.[2]

We present summary statistics of the weather and search variables in Tables 1 and 2. The weather variables are presented as deviations from the 10-year baseline covering 1994-2003, matched by state-calendar week. Relative to the 10-year baseline, 2004 through 2011 were similarly warm and slightly snowier, on average. As expected, weather varies substantially from week-to-week. One standard deviation in temperature corresponds to 3.3 degrees celsius deviation from the 10-year baseline. Summary statistics for the regression sub-sample for which we have complete weather and search data are very similar and are reported in the right-most columns of Tables 1.

In Table 2, we divide our sample by season. Relative to the 10-year baseline, winter has been slightly colder than normal, while spring, summer, and fall have been slightly warmer. The standard deviation of the temperature variable is of the same order of magnitude for all seasons, and suggests that there is considerable variation around the mean. As one would expect, snowfall and snow depth are most variable in the winter, somewhat less variable in the spring and fall, and quite tightly distributed in the summer.

## 2.2 Empirical Approach

In essence, we want to identify the effect of unusual short-run weather on the relevance of climate change in the eye of the general public, using the Google search intensity index outlined above as a proxy for salience. We take a largely agnostic stance on the mechanisms underlying a possible relationship. Weather could affect search intensity through channels such as personal experience, exposure to news coverage of extreme weather, or interactions with friends and family.[3]

We simultaneously estimate effects for the maximum temperature, precipitation, snowfall, and snow depth. Table 3 presents basic correlations among the explanatory variables. As one would expect, deviations in temperature, snowfall, and snow depth are correlated with one another. However, the frequency of our panel provides sufficient independent variation to estimate the coefficients on each precisely.

The base specification for state $s$, week $w$, month $m$, year $y$ can be expressed as:

$$INDEX_{s,wmy} = \sum_j \beta^j DEV^j_{s,wmy} + \alpha_{my} + \gamma_{sm} + \varepsilon_{s,wmy} \tag{1}$$

[2]Source: http://www1.ncdc.noaa.gov/pub/data/cmb/images/us/2012/jul/warmest_12months.png

[3]In a later section we examine the impact of adding different sets of fixed effects as a way to bound the importance of some of these mechanisms.

where $j$ indexes the four weather variables, $DEV^j_{s,wmy}$ is the deviation from the historical mean for measure $j$, $\beta^j$ is the effect of measure $j$ on the climate change search intensity index, and $\alpha_{ym}$ and $\gamma_{sm}$ are fixed effects. In our main specification, we relax the linearity of the relationship of the index on the deviation variables by allowing for asymmetric effects depending on the sign of the deviation:

$$INDEX_{s,wmy} = \sum_j \beta^{nj} NEGDEV^j_{s,wmy} + \sum_j \beta^{pj} POSDEV^j_{s,wmy} + \alpha_{my} + \gamma_{sm} + \varepsilon_{s,wmy} \quad (2)$$

where $NEGDEV^j = I(DEV^j < 0) * |DEV^j|$ and $POSDEV^j = I(DEV^j > 0) * |DEV^j|$. Thus, the coefficients $\{\beta^{nj}, \beta^{pj}\}$ are the effect of the *magnitude* of negative / positive deviation from the 10-year weather baseline on search intensity.

We graphically illustrate the basic idea behind our empirical strategy. Figure 3 plots kernel-smoothed time trends of the residuals of search index and average snowfall for Colorado from October 2006 through April 2007 after conditioning on year-month and state-month of year fixed effects. Through early December, snowfall tracks close to the 10-year baseline. In late December, relative search activity is halved contemporaneously with during a series of weeks with unusually high snowfall. However, as snowfall becomes more scarce in late January and February, search activity increases again.

A first potential concern with our analysis that Google searchers may not be representative of the general public. Past analyses such as Choi and Varian (2009) and Kahn and Kotchen (2010) suggest that Google search is sufficiently in the mainstream to be useful for this sort of analysis. In addition, we are not making claims as to whether local weather will help support for climate change reach some crucial electoral threshold. Rather, we examine whether very short-run weather events have the capability to affect the salience and prominence of climate change. Compared with 2010 Census data, the distribution of Google searchers skews away from those over 65 years of age, and toward those 18-25. The shares in the 25-44 and 45-65 age groups are roughly the same as in the population.[4]

In addition, one might be concerned that there may be underlying seasonal or geographic correlations that are purely coincidental. For instance, as displayed in Table 1, recent summers have been hot compared with historical means while recent winters have not. During our sample period, the Conference of the Parties to the United Nations Framework Convention on Climate Change convened during November and December in each year. If this highly climate-relevant

[4] Google search demographics from comScore, via http://blog.pmdigital.com/2010/08/who-uses-google-yahoo-and-bing. Census demographics from http://www.census.gov/prod/cen2010/briefs/c2010br-03.pdf

event results in a spike in news coverage and search activity, we would incorrectly estimate a negative relationship between maximum temperature and climate search intensity. Similarly, if states with more urban areas have had systematically different weather deviations than more rural states, we might misattribute a correlation between weather differences and differences in political ideology as reflected in interest in climate change.

To address these concerns, we employ a variety of fixed effects to control for such possible sources of bias. In our preferred specification, we include year-month fixed effects and state-month of year fixed effects. The variation identifying our primary estimates controls for broad national trends during a given month, and monthly seasonality at the state level. For a given January week in Iowa, we consider the covariance in how unusual search and weather are among all January weeks in Iowa, controlling for nationwide means in that specific month. The year-month effects capture changes in nationwide attitudes toward climate change, average internet penetration, and changes in the makeup of internet users over time. The state-month of year effects control for seasonality in weather deviations and climate change search intensity.

Finally, one might be concerned that search activity by climate skeptics could contaminate the interpretation of our coefficients. In Figure 4, we compare the national time-series of our primary search with one that nets out several potential skeptical searches. As is clear from the figure, these searches comprise a very small fraction of the total searches. The window indicated in the figure does display some skeptical search activity: it corresponds to the "Climategate" incident. Our results are robust to omitting this period.

# 3 Weather and Search Intensity Results

The results from the base specification are presented in Table 4. The first column is a simple specification in which climate-related search intensity is modeled as a linear function of deviations from historical weather patterns. Perhaps surprisingly, in the aggregate, higher temperatures (relative to the baseline) are associated with lower search intensity. The coefficient on snowfall is as expected, in that unusually low snowfall is related to more climate change searches.

We relax the initial specification in two ways. First, we allow the coefficients to vary by season of the year in columns (2) - (5) of Table 4. This allows the effects of unusual weather on search intensity to have the different magnitude or sign across seasons. For example, unusually warm weather in the winter might be far more noticeable in the winter than in the spring. We find the effects vary considerably by season. While lower temperatures are still negatively related to search in the winter, the opposite is true in the summer. The effect of unusually low snow depth is now statistically significant in the winter and fall, but not in the spring (or summer).[5]

Second, we allow the effect of weather to vary asymmetrically with respect to positive and negative deviations from the 10-year baseline. Although results from Table 4 provide evidence that short-run weather shocks are correlated with search intensity, if search intensity responds differently positive and negative deviations from the baseline, our specifications in Table 4 may mask the true effect. The bias would be particularly pronounced if search intensity is a function of the absolute deviation of weather from the long run average. To this end, Table 5 presents results that allow positive and negative weather deviations to have asymmetric linear effects on search intensity. To be clear, our specification regresses search intensity on the absolute value of positive and negative deviations. If the coefficients for the positive and the negative deviation in snowfall are both positive, then the relationship between snowfall and search intensity is "V"-shaped.

For ease of comparison, column (1) is identical to column (1) in Table 4. Column (2) presents the asymmetric estimates when data from all seasons are pooled. Both positive and negative deviations from the long-run average are positively associated with search intensity. The negative coefficient from column (1) is driven by the fact that the search-inducing effect of a negative deviation dominates the effect of a positive deviation. Search intensity seems to respond weakly to unusually dry weather. The coefficients on snowfall and snow depth especially illustrate the importance of allowing for asymmetric effects. We find little affect of abundant snowfall and snow depth on climate searches. This is not a surprising result: it is unclear why normal weather should result in *more* search activity than unusually snowy weather. This flexibility also isolates the effect of a lack of snow. The coefficients on negative deviations in snowfall and snow depth are roughly four times larger than their counterparts in column (1), and the coefficient on snow depth is now statistically significant.

We again run separate regressions for each season; the estimates are presented in columns (3)-(6). We interpret the magnitude of the coefficients in the following manner. The search index is simply the number of searches involving climate change or global warming as a share of total search activity, scaled by some unknown coefficient. We assume that climate-related searches are a small proportion of total search activity. Thus, a 10% increase in the search

[5]For completeness, we also present coefficients for each month of the year in the Appendix. Providing further flexibility in estimate the coefficients by month does not provide an additional insights beyond the estimation by season.

index corresponds to a 10% increase in climate-related searches. We will consider the effect of weather shocks on the mean week in percentage terms. For instance, in the winter, the mean search index if 0.4302. An increase of 0.043 in the winter would correspond to a 10% increase in climate-related search over the mean week.

As before, we find substantial variation in the effect of abnormal weather across seasons. In the winter, search intensity responds positively to both unusually cold and warm weather. In particular, a winter week that is 4°C colder than normal (1 standard deviation of our temperature variable) would result in an increase in the search index of 0.066, or a 15.3% increase in cliamte-related search activity relative to the mean week. Similarly, a week that is 4°C warmer than normal would result in an increase in the search index of 0.022, or about 5.1%. Much of the effect of warm winter weather operates through a lack of snowfall. Indeed, a winter week that has less snowfall than average by only 1cm (roughly 1 standard deviation) is also associated with an increase of roughly 0.026 (6.0%) in the search index; a week in which the average snow depth is lower than usual by 1 standard deviation (roughly 7cm each day) is associated with an increase of 0.056 (13.0%) in the search intensity. These magnitudes suggest that weather shocks are actually responsible for fairly large movements in climate-related search activity relative to the mean week.

Search also responds somewhat to both unusually wet and dry weather. Altogether, a week with unusually warm weather and little snow would result in a modest, but significant short-run change in search intensity. In a later section, we consider the persistence of these effects in the medium-run. In many cases, it turns out that the medium-run effect is larger than the short-run effect.

Responses during other seasons demonstrate different patterns. In the spring, weather does not actually seem to have much of an impact: none of the coefficients are statistically significant. This confirms a main result of Deryugina (forthcoming), who finds that beliefs elicited in a March survey are not affected by very short-run weather deviations. In the summer, search responds strongly to extremely hot temperatures, but not too cool temperatures. Positive deviations in snowfall (albeit rare) are associated with more search, while negative deviations in precipitation are associated with less search. Finally, in the fall search increases with unusually low snowfall and snow depth. This is consistent with search responding to steadily warm fall weather that delays the first snowfall or a heat wave that results in unexpectedly extreme temperatures.

## 3.1 Persistence

The results from the main specification provide evidence that people respond contemporaneously to the current weather. However, we might suspect that these effects are persistent; that is, along with today's weather, a prolonged heat wave or lack of snowfall could also affect today's search intensity. Indeed, Deryugina (forthcoming) finds longer periods of unusual weather to have a bigger impact than short-run deviations. We examine the medium-run effects of weather on search intensity across seasons. We augment our main specification with four weeks of lags on the weather variables. Because snow depth has an inherently dynamic component that is a function of recent snowfall and temperatures, we omit it from the dynamic specification. The results are presented in Table 6. The p-values at the bottom of each column are from F-tests that the sum of the contemporaneous effect and all included lags is equal to zero.

Like contemporaneous variables, we find that the effect of weather on search intensity varies in its persistence across measures and seasons. In the winter, the effect of a negative deviation in snowfall is somewhat persistent, with individually significant coefficients for the last 2 weeks of snowfall. This is also true of negative deviations in maximum temperature. The effect of positive deviations in maximum temperature do not exhibit a consistence sign. Although warm weather today increases search intensity, warm weather in the two weeks prior has a negative effect. However, warm weather three and four weeks ago more than offset this. The overall effect of a warm week is that it will increase search activity over the subsequent month.

In the spring, find little evidence of medium-run persistence. In the summer, a warm week has a large and statistically significant and positive effect on search activity contemporaneously and for the following two weeks. This is true in the fall, except that the main effects are felt a couple of weeks in the future. Unusually low snowfall in the fall has a persistent effect akin to that observed in the winter.

The dynamic decompositions provide additional insight into the main effects. It appears that the lagged effects partially reflect the fluid nature of the seasons. For instance, although unusually warm weather in the fall is not significant contemporaneously, lagged warm weather is. This suggests that a heat wave at the end of the summer could have an effect on search intensity that spills over into the fall. Such dynamics demonstrate the importance of analyzing response to weather throughout the entire year.

### 3.2 National and local weather

Our main specifications include year-month and state-month of year fixed effects. The impact of weather on search has been identified off of within-state variation, controlling for state-specific seasonality and nationwide variation for the month. This is our preferred specification because it allows us to effectively compare observations with similar local conditions, while controlling for broad trends in weather and search intensity. However, we present the results using other sets of fixed effects in Table 7.

Although the coefficients do change in magnitude across the specifications, they are remarkably robust. By comparing magnitudes, we can explore the relative importance of local and national variation in weather. Internet searches related to climate change may be driven by a combination of local and national weather. In addition, weather is likely to be correlated in the cross-section. If there is a heatwave in Iowa, it is likely that Ohio will be experiencing unusually hot weather as well. In this case, part of the search response in Iowa will be due to personal experience with the unusual weather and local media coverage. However, some of the response will also be due to interactions with family and friends in Ohio and regional or national news coverage of the broader heatwave. Our preferred specification includes year-month fixed effects and does not exploit national variation in weather. By comparing estimates with different sets of fixed effects, we can gauge the relative importance of local versus national trends.

In Column 4, we reproduce our preferred specification, with year-month fixed effects. These control for short-run nationwide events, such as a major heatwave or drought. Relative to the specification in column 3 which only include year fixed effects, the coefficients on the temperature deviation variables fall in magnitude by roughly 20%. This suggests that a part of our estimated weather-search effect may be driven by spillovers from national events and trends.

As we move through the columns, we add various richer combinations of fixed effects. We present our most flexible specification in Column 7. Here we allow for unobservables at the year-week and state-week of year level. Even after netting out all national variation in search intensity and weather, we get very similar results to our preferred specification.

In Figure 5, we plot the year-week fixed effects from Column 7 in Panel A. Panel B shows the weekly average deviation in maximum temperature across the sample. Clearly, some level of nationwide time fixed effect is important for proper estimation. The four red lines signify peaks in the fixed effects corresponding to important climate-related news events: Hurricane Katrina, the release of the 2007 IPCC report[6], the *Massachusetts v. EPA* Supreme Court Clean Air Act

[6] This report stated that climate change since the mid-20th Century is anthropogenic with greater than 90% confidence.

ruling, and the "Climategate" scandal of late 2009.

Looking at Panel B, it is clear that Hurricane Katrina happened in a week that was unusually warm across the county, while Climategate (coincidentally) was followed by an unusually cold week. Controlling for such correlations, ensures that we do not pick up search activity driven by contemporaneous nationwide news coverage and weather events.

Finally, our main specification uses state-level variation in weather and search intensity. Because the weather stations are not weighted by nearby population or search activity, we may measure weather with measurement error. In the case of small states such as Rhode Island, a state-level analysis might be a reasonable aggregation; however, a state like California is climatically, politically, and economically diverse. Luckily, the Google Insights tool also reports search intensity at the city level for major U.S. metropolitan areas. As a check, we also perform our analysis on the 25 largest U.S. cities as grouped by Google Insights. Table 8 presents estimates from regressions that include year-month and city-month of year fixed effects; that is, they are analogous to our preferred state-level estimates from Table 5. The results reveal that the city-level relationships are quite similar to those found at the state level. That is, even when we restrict our data to a set of metropolitan areas, the relationship between weather and search intensity holds.

## 4 Heterogeneous Response to Weather

Finally, we separate states by their economic reliance on two weatehr-sensitive industries: farming and winter tourism.[7] We posit that internet search related to climate change may be more driven by weather that affects the local economy. As noted in a recent *Denver Post* column, "...it has become somewhat predictable that with the first sign of a lack of natural snow, climate change articles and stories start to appear. In many ways, it's to be expected. It's hard to understand how the weather changes the way it does and why things can look so different from year to year." [8] We also identify states with strong preferences for the environment using the average League of Conservation Voters score of the state's congressional delegation as a proxy. States falling into each of these categories are likely to systematically differ across other characteristics as well; these results should be interpreted as descriptive. However, there is substantial, but not complete, overlap across these three different dimensions. This overlap gives us some

[7]We identify farming-states as states with more than 1% of gross state product (GSP) that comes from farming (i.e., NAICS industry 104) based on data from the Bureau of Economics Analysis. Ski-states in the top quartile of the number of ski areas operating in 2010-2011, as reported by the National Ski Areas Association.

[8]Source: "Skiing won't be greatest loss after climate change", Rob Katz, Dec. 12, 2012.

confidence that these categorizations are not completely driven by unobserved characteristics.

We examine the economic makeup of states to probe potential interactions between weather and the political economy of the climate debate. During past legislative efforts to reduce carbon emissions such as the Waxman-Markey bill, a major opponent of the legislation was the set of coal-producing states. These states were concerned that pricing carbon would have a deleterious effect on their states' economies. We hypothesize that there may be an opposing effect in states whose industries may be adversely affected by a *lack* of climate policy. Differential responses to weather in terms of search intensity would be suggest potential for such an effect.

In Table 9, we allow for heterogeneous responses based on whether farming accounts for more than 1% of GSP on average in our sample years. One striking difference is that farming states respond more strongly to negative temperature deviations in winter and spring months.[9] In contrast, search intensity in non-farm states is *negatively* correlated with negative temperature deviations in the spring. This is consistent with a story in which states depending on agriculture are particularly sensitive to late frost. The effect of hot summer temperatures on search appears to be driven by non-farm states. With respect to precipitation, positive deviations in winter, spring, and autumn snowfall reduce search intensity in farm states, but not in non-farm states. These differences are statistically significant, and could be driven by the effect of snowpack on water availability. Interestingly, there is little difference in response to rainfall.

We also examine ski states, which we define as those in the top quartile in terms of number of ski areas. Indeed, the significantly different coefficients are snow-related. The significant coefficient on snow depth in the full sample is entirely driven by ski states. Ski states respond to negative deviations in snow depth in fall and winter (i.e., ski season) with increases in search intensity. In contrast, the response of non-ski states is not significantly different from zero. The response to unusually low snowfall, which is less relevant to ski slopes conditional on snow depth, is not significantly different across the two groups of states. Positive deviations in spring snowfall and snow depth, which would indicate an unusually long ski season, both have a significantly larger effect in ski states.

Finally, Deryugina (forthcoming) and Hamilton and Stampone (forthcoming) suggest that people of different political persuasions respond differently to weather cues in forming climate perceptions. Although we cannot distinguish searches by an individual's party affiliation, we allow for heterogeneous search effects based on the importance that a state places on environmental issues, as revealed by the voting behavior of its House delegation. For each state's

[9] Appendix tables A4, A5, and A6 present magnitudes and statistical significance of differences in the heterogeneous coefficients for farm, skiing, and green states, respectively.

delegation, we calculate the average LCV rating during 2004-2011.[10] Green states are defined as those in the top quartile. We find that the green states are driving much of the response to warm temperatures in the winter and fall; similarly, green states are more responsive to an unusual scarcity of snow in the winter. In contrast, Deryugina (forthcoming) finds that only conservatives are responsive to weather, and Hamilton and Stampone (forthcoming) who finds that only political independents respond. A possible explanation for this difference is that we consider aggregate responses; the previous studies measure the response of an individual. It is entirely possible that the marginal people that are induced to search by a weather shock are the independent or conservatives in these majority-environmentalist states. In addition, the "political treatment effect" may be different depending on whether we are measuring salience or opinion. Our analysis measures salience as revealed by search activity, while previous studies measure belief in climate change when prompted by an interviewer. Both components of public opinion are important for policy consideration.

## 5 Weather, Search Intensity and Voting Behavior

Finally, we demonstrate that atypical weather and search intensity are correlated with observable action on environmental issues, specifically the voting behavior of members of the U.S. Congress. A long literature in political science suggests issue salience plays an important role in voter engagement (Brians and Wattenberg (1996)), attitudes towards elected officials (George Edwards and Welch (1995)) and policymaking (Burstein (2003)). We extend our approach from the previous section to examine whether weather (and search behavior as a proxy) influence the voting behavior of members of the U.S. Congress.

Our main voting data is drawn from LCV scorecards. For each member of Congress and each vote on bills, resolutions, motions and amendments related to the environment, the LCV records a member's vote and identifies whether the vote represents a pro- or anti-environment position. For our analysis, we use member-level votes on all 215 environmental votes tracked by the LCV between 2004 and 2011.

Unsurprisingly, Democrats tend to receive high LCV ratings and Republicans tend to receive low LCV ratings – the mean ratings for Democrats and Republicans are 89.7 and 14.1 on a scale of 0 (uniform voting against environmental positions) to 100 (uniform voting in favor of environmental positions). Perhaps more surprisingly, LCV scores vary within political party substantially. Of congressional members in office for more than a single year in the 2004-2011

[10] http://www.lcv.org/scorecard/scorecard-archives/

period, Dan Boren (House, OK) was the lowest rated Democrat at 32.7 and Christopher Shays (House, CT) was the highest rated Republican at 88.1. LCV Scorecards (and voting scorecards more generally) have been used extensively in the literature (see e.g., Kahn (2002), Levitt (1996), Kalt and Zupan (1984)) to identify members of Congress who tend to take pro- or anti-environmental stances.

We use a linear probability model and regress pro-environment voting as a function of weather in a member's home state. Based on the results in the previous section, we focus on positive and negative deviations of maximum temperature and snowfall.[11] All specifications include congressional member fixed effects. Consequently, identification comes from within-member variation – we test whether member $i$'s vote on environmental vote $v$ is correlated with anomalous weather conditions in their home state $s$ at a similar point in time $t$.

$$Pro-Env.\ Vote_{i,v} = \alpha_i + \sum_j \beta^{nj} NEGDEV^j_{s,t} + \sum_j \beta^{pj} POSDEV^j_{s,t} + \varepsilon_{i,v} \tag{3}$$

where $j$ denotes each weather variable and $NEGDEV^j_{s,t}$ and $POSDEV^j_{s,t}$ represent positive and negative deviations from the 10-year baseline.

As a second approach, we use search intensity as a summary statistic for the weather variables. Since the weather variables are correlated, using search intensity rather than the set of weather variables gives us substantially more power with which to estimate the effects of interest. The primary concern with search intensity entering directly into (3) in place of the weather variables is reverse causality. If internet searches related to climate change are partially driven by actions taken by Congress or by the voting of particular members, a positive correlation between search intensity and Congressional voting may simply reflect constituents interest in the position taken by their representative. To address this concern, we project search intensity in a state onto four lags of the local climate deviations for temperature, precipitation, snowfall and snow depth. Consequently, the "second-stage" only relies on variation in search intensity correlated with lagged weather variables.

$$SI_{s,t} = \gamma_s + \sum_{k=1}^{4} \sum_j \lambda^{njk} NEGDEV^j_{s,t-k} + \sum_{k=1}^{4} \sum_j \lambda^{pjk} POSDEV^j_{s,t-k} + \nu_{s,t} \tag{4}$$

$$Pro-Env.\ Vote_{i,v} = \alpha_i + \beta \widehat{SI}_{s,t} + \varepsilon_{i,v} \tag{5}$$

Table 12 presents the main results relating voting on environmental issues to weather and

[11] We obtain qualitatively similar results using a probit model.

search intensity. Columns (1) through (3) present the results regressing a dummy variable for pro-environment voting on weather, member fixed effects and successive sets of time fixed effects. Unusually low temperatures in a member's home state are correlated with votes a greater likelihood of voting against environmental legislation or motions. Unusually low snowfall in a member's home state is correlated with an increased likelihood of voting in favor. The magnitudes are modest but significant and persist with the inclusion of year-month fixed effects that subsume the effect of national weather or news spuriously correlated with weather that occurs in the month of the environmental vote. Snowfall one standard deviation below the mean during winter months in associated with an 1.5 percentage point increase in the likelihood of voting in favor of environmental legislation.

Columns (4) through (6) present the coefficients estimated by (5), using member fixed effects and a similar series of time fixed effects. Again, we find that the weather-correlated component of search intensity is correlated with voting in favor of environmental legislation – a one standard deviation increase in search intensity (.22) is associated with a 6.6 percentage point increase in the likelihood of voting in favor of environmental legislation. As with the weather variables, the magnitude of the coefficient declines with the inclusion of finer time fixed effects. Month by year fixed effects subsume the effect of national weather events, such as the 2012 U.S. summer heatwave – identifying the coefficient off of within-month variation only, a one standard deviation increase in search intensity is associated with a 1.8 percentage point increase in the likelihood of voting in favor of environmental legislation. As a point of reference, Hussain and Laband (2005) examine 33 LCV votes whose costs are confined to a small set of states. Senators who represent one of those states are 15% less likely to cast a pro-environment vote. Given the extreme political circumstances involved in those votes, our effect (one-eighth as large for a 1 standard deviation increase in search, one-quarter as large for a 2 standard deviation increase in search) appears non-negligible.

One concern with these results is that the timing of votes may be endogenous. All of our previous results condition on an environmental vote being held – for endogeneity to spuriously drive our results, Congress would have to schedule favored environmental votes in weeks following extreme weather and unfavored environmental votes in other weeks. Because we only include year-month and member fixed effects, our identification strategy would be vulnerable to such a phenomenon. Although we cannot observe whether a particular environmental vote is preferred for other reasons, we can examine whether the timing of environmental votes seems to follow extreme weather overall. We regress contemporaneous and one-week lagged weather deviations on an indicator for whether an LCV vote occurred, controlling for year-month and state fixed effects. The idea is to compare weeks within a calendar month, and see if LCV votes happen following weeks with more extreme weather. We do not find evidence that this is the case. Given this finding, reverse causality would only be problematic if those environmental votes that are inherently more favored overall also tend to be scheduled after especially extreme weeks of weather.

A second concern are other factors that might drive a spurious relationship between the timing of votes and unusual weather. For example, if public sentiment in a state (or nationally) is shifting from one party to another at the same time as unusual weather, the results in Table 12 above may simply reflect a spurious correlation between the two. Although the specifications with month-year fixed effects subsume the effect of national weather as well as trends in national political preferences, it is still possible that local weather is spuriously correlated with changing political preferences at the state-level and hence, within-member voting on environmental legislation.

As a test for this type of spurious correlation, we examine voting data from the American Conservative Union (ACU). Similar to the LCV, the ACU tracks "a wide range of issues before Congress to determine which issues and votes serve as a dividing line to help separate those members of the U.S. House and Senate who protect liberty as conservatives and those who are truly liberal."[12] Votes reported by ACU from 2004 to 2011 include forty-four votes related to the environment issues that are also tracked by the LCV (e.g. HR 2643: Allowing the Dept. of the Interior to issue new leases for offshore natural gas development) as well as votes related to immigration, the minimum wage, family planning, religious freedom and other issues unrelated to the environment. For the placebo test, we use data from only the 350 non-environmental votes tracked by the ACU between 2004 and 2011.

If general political preferences are shifting at the same time as unusual weather, we should expect that the weather-correlated variation in search intensity would be correlated with voting on non-environmental votes tracked by the ACU. We replicate the specifications in columns (4) through (6) of Table 12 using Congressional member voting on non-environmental issues tracked by the ACU. Table 13 presents the results – columns (1) through (3) use all of the non-environmental votes tracked by the ACU; columns (4) through (6) use only the non-environmental votes tracked by the ACU that occur in the *same week* as the environmental votes tracked by the LCV. We do not find the weather-correlated component of search intensity

[12] http://conservative.org/legislative-ratings/

to be closely correlated with taking liberal or conservative positions on votes unrelated to the environment, even when restricting the set of votes to those occurring in the same week as the LCV votes. This suggests that our results are not being driven by changes in *general* voter preferences that are spuriously correlated with unusual weather.

Finally, in Table 14 we test whether the strength of the correlation between search intensity and voting behavior differs by the characteristics of the Congressional member. We interact the weather-correlated component of search intensity with whether the member of Congress is a Democrat, a member of the Senate, and with the member's LCV score over the 2004-2011 period. In four of the six specifications, we find that the correlation between anomalous weather in a member's home state and voting on environmental legislation is stronger in the House than the Senate. This possibly reflects the benefit of the six-year terms in the Senate, which may make Senators less responsive to short-lived changes in constituent interests. We find that the magnitude of the effect also differs by political affiliation. The correlation between voting and home-state search intensity is significantly stronger for Democrats. In columns (4) through (6), we estimate interaction terms separately by ten-percentage point bins of LCV ratings. With the inclusion of member-fixed effects, the coefficients on the interaction terms reflect the correlation between voting and home-state search intensity, conditional on a member's average level of support for environmental legislation. Thus, positive values indicate that a member is more likely to take a pro-environment stance when home-state search intensity is high and less likely to take a pro-environment stance when home-state search intensity is low. We find no strong evidence of correlation between voting and home-state search intensity for members with LCV ratings below 50 percent, but find a positive and significant relationship for members that take a pro-environment stance more than half the time. Unsurprisingly, the correlation diminishes for members with very high LCV ratings – these members almost always vote in favor of environment legislation.

It is important to qualify the results above in two respects. First, the correlation between voting and search intensity reflects the voting of individuals members, conditional on the actual legislation brought to a vote. While we find that members of Congress (and in particular, Democrats) are more likely to vote in favor of environmental regulation when home-state relative search intensity for global warming or climate change tends to be high, we cannot assess whether this implies discrete changes in the passage of legislation or the changes in the content of legislation brought to a vote. Most of the votes tracked by the LCV were passed or defeated with substantial support; in these cases, the vote of a single member is unlikely to be marginal ex-ante and members of Congress may have more latitude to take a position contrary to the position of their party. Only 15 percent of the votes tracked by LCV were passed (or defeated) by less than a five percentage point margin. Members (and caucuses) may behave differently for votes close to passage or defeat. We nonetheless feel that the observed relationship to marginal voting behavior is meaningful. The relationship illustrates that abnormal weather or high search intensity are related to important, observable behavior on environmental issues. Although the political economy of the legislative process makes it unlikely that the marginal effect of an individual Congressional member would translate into discrete changes in policy, our results suggest that search activity may be a useful proxy for constituent concern and the salience of particular policy issues.

Second, while we identify an effect of abnormal weather on pro-environment voting, it is beyond the scope of our existing data to map a clear causal chain from weather and search activity to legislative action. As the previous literature ( Kahn (2002), Levitt (1996), Kalt and Zupan (1984)) notes, many factors drive the voting of legislators, from ideological preferences and interactions with concerned constituents to longer-run concerns about re-election and the ability to generate campaign contributions. That said, the short run nature of our identifying variation does suggest that the effect is not entirely driven by consistent ideological preferences or a desire to demonstrate a *consistent* pro-environment stance to voters.

# 6 Conclusion

Anthropogenic climate change remains a societal threat and major policy challenge. Public opinion on the existence and severity of climate change has fluctuated considerably over recent decades. Forming accurate beliefs about a long-term one-time event such as climate change places an enormous informational burden on the actor. A natural proxy for understanding climate change is a short-run weather event. Indeed, Hansen et al. (2012) describe the effect of climate change as changing the weights on a pair of dice that determine short-run realizations of weather.

This paper tests the extent to which the salience of climate change is affected by such short-run weather deviations. We use Google Insights search data to proxy for salience, which allows us to perform our analysis at the state-week level. We find that search intensity does indeed respond to weather deviations. Further, the high temporal resolution of our data allows us to provide a number of novel insights. First, the effect of weather on search intensity varies substantially across the seasons. Unusually cold temperatures have a large effect only in the fall and winter; unusually warm weeks are associated with increased search only in the winter and summer. There does not appear to be much of a relationship between spring weather and search. Second, states identified as having a prominent climate-sensitive industry tend to respond differently in expected ways. For instance, farming states are sensitive to unusually cold spring weather, while ski states are more sensitive to unusually low snow depth. Third, we find that states with stronger environmental preferences are generally more responsive to weather shocks.

We demonstrate that similar patterns exist in the environmental voting record of members of the U.S. Congress. We find that members, and in particular Democrats, are more likely to vote in favor of environmental legislation when their home state experiences anomalous weather or high search activity related to global warming and climate change. While modest in size, the results provide an important, policy-relevant link between anomalous weather and observable action on environmental issues. In addition, the results suggest that search activity may be a useful proxy for the concerns of local constituents, an important political consideration that is typically difficult to assess.

# References

**Brians, Craig and Martin Wattenberg**, "Campaign Issue Knowledge and Salience: Comparing Reception from TV Commercials, TV News and Newspapers," *American Journal of Political Science*, 1996, *40.*

**Burstein, Paul**, "The Impact of Public Opinion on Public Policy: A Review and an Agenda," *Political Research Quarterly*, 2003, *56.*

**Choi, Hyunyoung and Hal Varian**, "Predicting the Present with Google Trends," 2009. Mimeo, Google Inc.

**Deryugina, Tatyana**, "How do people update? The effects of local weather fluctuations on beliefs about global warming," *Climatic Change*, forthcoming.

**Edwards, William Mitchell George and Reed Welch**, "Explaining Presidential Approval: The Significance of Issue Salience," *American Journal of Political Science*, 1995, *39.*

**Egan, Patrick J. and Megan Mullin**, "Turning Personal Experience into Political Attitudes: The Effect of Local Weather on Americans' Perceptions about Global Warming," *Journal of Politics*, 2012.

**Hamilton, Lawrence C. and Mary D. Stampone**, "Blowin' in the Wind: Short-term Weather and Belief in Anthropogenic Climate Change," *Weather, Climate, and Society*, forthcoming.

**Hansen, James, Makiko Sato, and Reto Ruedy**, "Perception of Climate Change," *Proceedings of the National Acadamies of Sciences*, 2012, *109*, 14720–14721.

**Hussain, Anwar and David N. Laband**, "The tragedy of the political commons: Evidence from U.S. Senate roll call votes on environmental protection," *Public Choice*, 2005, *124*, 353–364.

**Kahn, Matthew E.**, "Demographic Change and the Demand for Environmental Regulation," *Journal of Policy Analysis and Management,*, 2002, *21*, 45–62.

_ **and Matthew J. Kotchen**, "Environmental Concern and the Business Cycle: The Chilling Effect of Recession," 2010. NBER Working Paper 16241.

**Kalt, Joseph P. and Mark A. Zupan**, "Capture and Ideology in the Economy Theory of Politics," *American Economic Review,*, 1984, *74*, 279–300.

**Levitt, Steven D.**, "How Do Senators Vote? Disentangling the Role fo Voter Preferences, Party Affiliation and Senator Ideology," *American Economic Review,*, 1996, *86*, 425–441.

**Owen, Ann L., Emily Conover, Julio Videras, and Stephen Wu**, "Heat Waves, Droughts, and Preferences for Environmental Policy," 2012. Mimeo, Hamilton College.

**Stephens-Davidowitz, Seth**, "The Effects of Racial Animus on Voting: Evidence Using Google Search Data," 2011. Mimeo, Harvard University.

## Tables and Figures

Figure 1: Average temperature deviations, 1974-2011

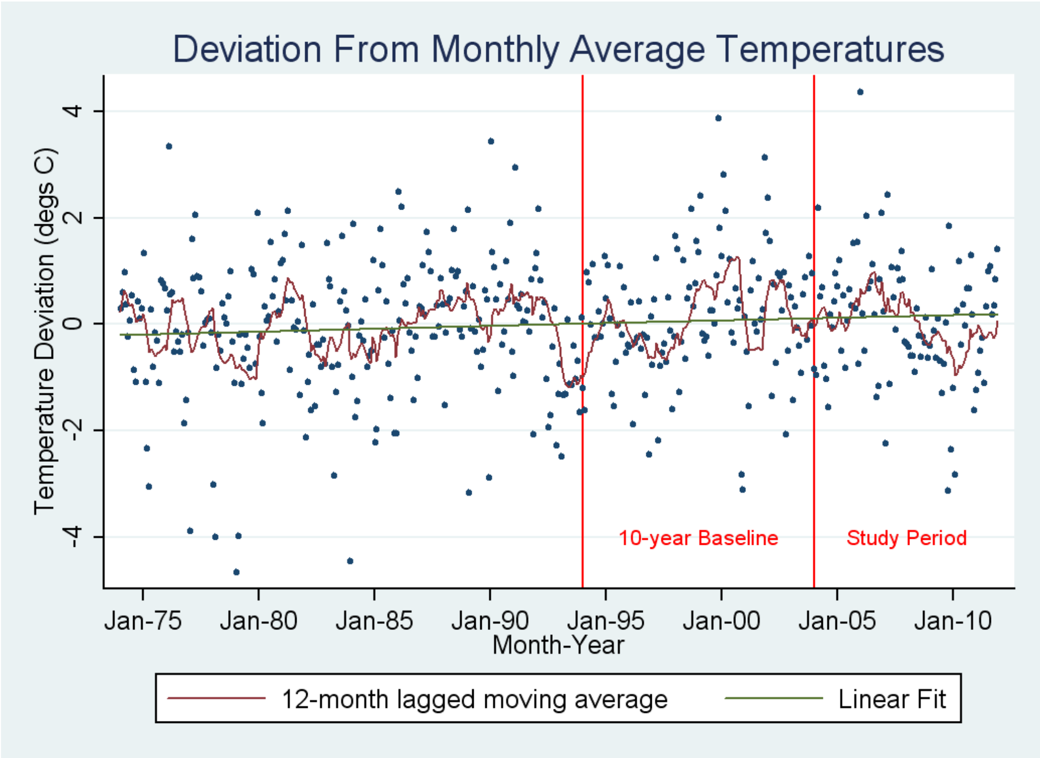

Figure 2: Average temperature deviations, 10-year baseline and study period (1994-2011)

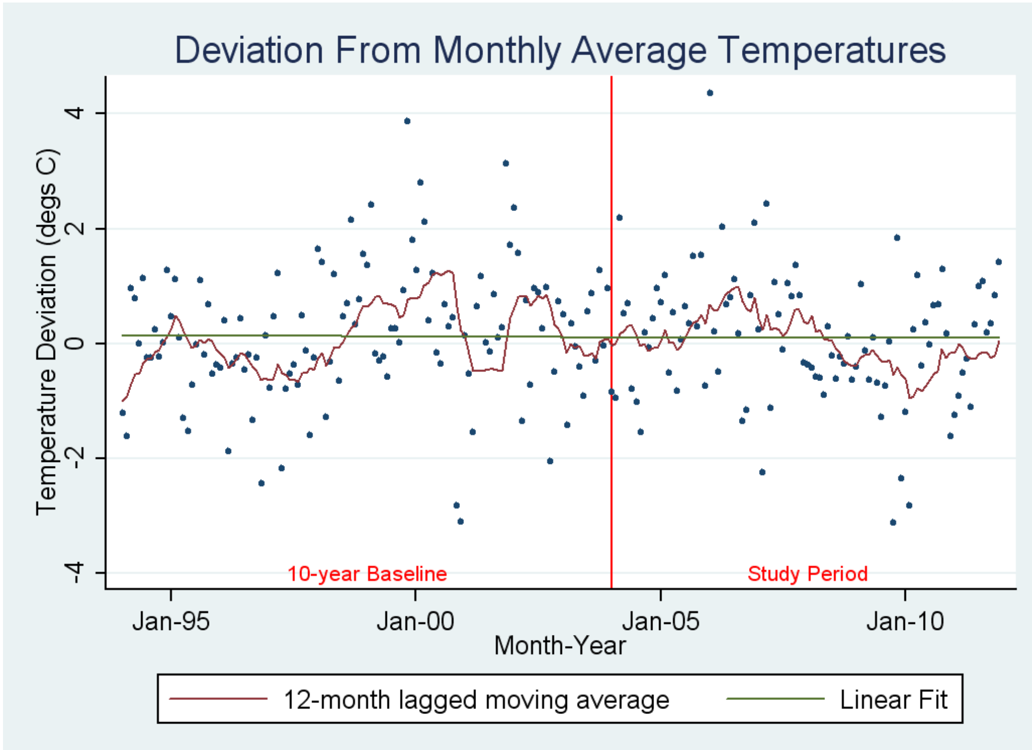


Figure 3: Plot of residuals: Colorado, Oct. 2006-Apr. 2007

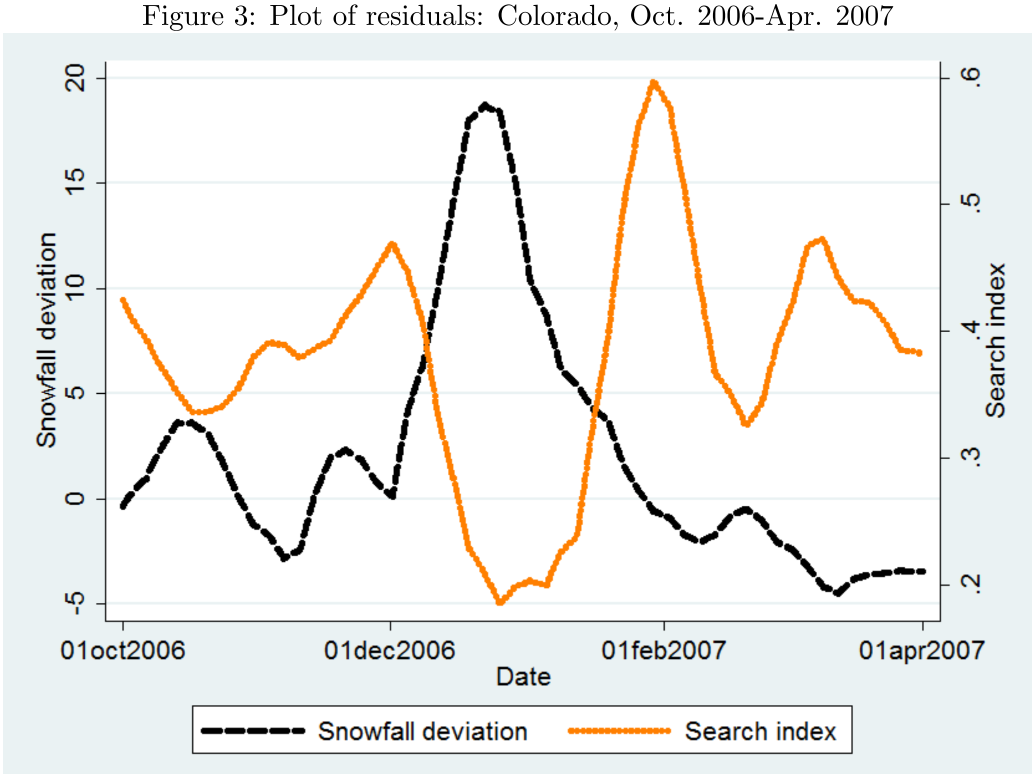

Figure 4: Relative search volume with and without skeptics

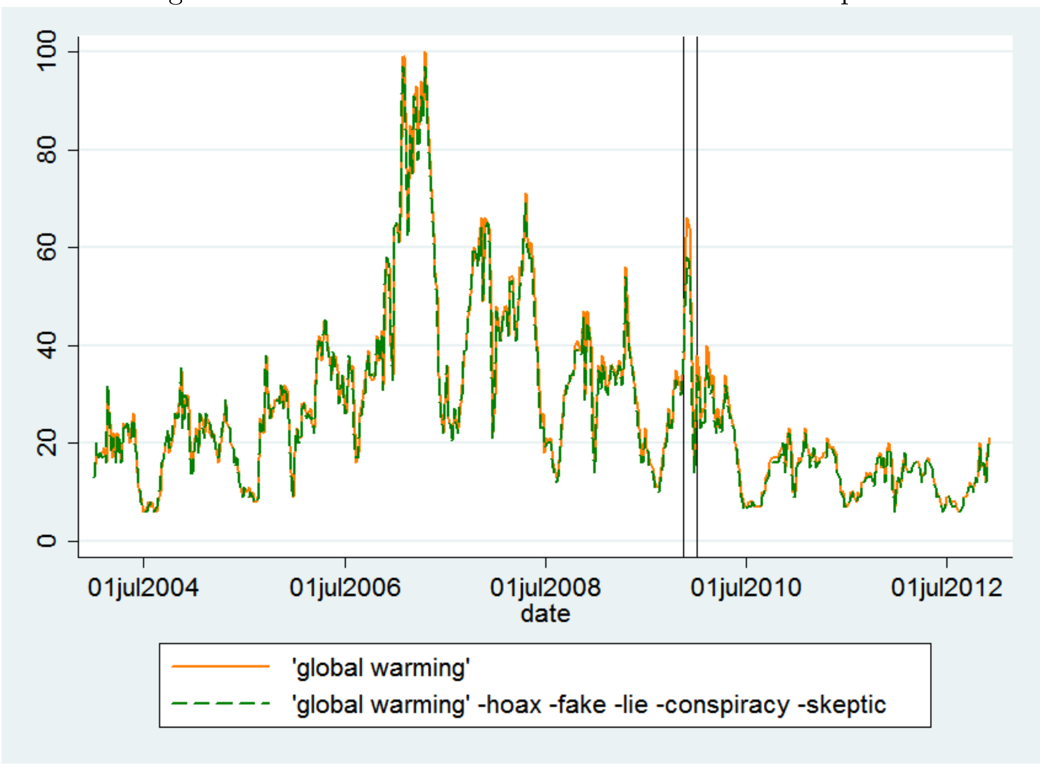

Figure 5: Year-week fixed effects

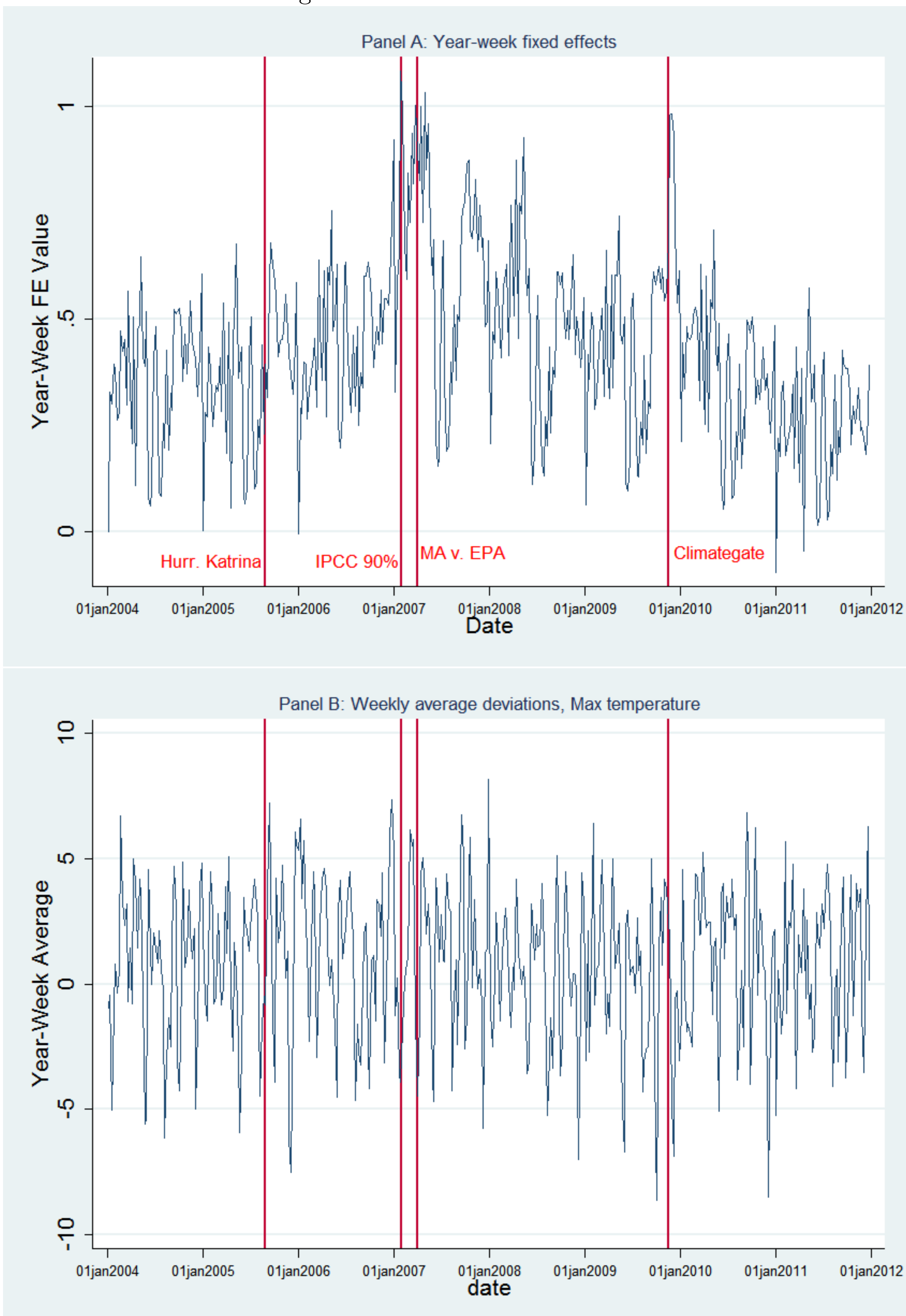

Table 1: Descriptive Statistics, Full Sample

| | All | | | Regression sample | | |
|---|---|---|---|---|---|---|
| | Mean | SD | N | Mean | SD | N |
| Maximum Temperature (°C) | -0.0201 | 3.2408 | 21267 | -0.0331 | 3.2633 | 16546 |
| Precipitation (mm) | 0.1104 | 2.6922 | 21267 | 0.1044 | 2.7115 | 16546 |
| Snowfall (mm) | 0.3263 | 5.6607 | 21220 | 0.4892 | 6.0449 | 16546 |
| Snow Depth (mm) | 3.4206 | 40.096 | 21264 | 4.3219 | 42.619 | 16546 |
| Google Search Index | 0.3963 | 0.2825 | 16596 | 0.3965 | 0.2828 | 16546 |

Notes: All weather variables are deviations from the 10-year baseline covering 1994-2003. Sample period is from 2004-2011.

Table 2: Descriptive Statistics by Season

| | Winter | | Spring | | Summer | | Fall | |
|---|---|---|---|---|---|---|---|---|
| | Mean | SD | Mean | SD | Mean | SD | Mean | SD |
| Maximum Temperature (°C) | -0.7083 | 4.0552 | 0.2705 | 3.2284 | 0.1994 | 2.1956 | 0.1371 | 3.0479 |
| Precipitation (mm) | -0.0260 | 2.4107 | 0.1031 | 2.7223 | 0.1362 | 2.6152 | 0.2055 | 3.0242 |
| Snowfall (mm) | 1.7908 | 10.141 | 0.0685 | 4.8793 | 0.0006 | 0.0525 | 0.0337 | 3.4447 |
| Snow Depth (mm) | 14.411 | 73.259 | 2.8974 | 37.368 | 0.2317 | 3.7803 | -0.7467 | 10.026 |
| Google Search Index | 0.4302 | 0.2964 | 0.4710 | 0.3049 | 0.2332 | 0.1644 | 0.4196 | 0.2711 |
| N (Regression Sample) | 4269 | | 4320 | | 3485 | | 4472 | |

Notes: All weather variables are deviations from the 10-year baseline covering 1994-2003. Sample period is from 2004-2011.

Table 3: Weather correlations

| | Max temp | Precip | Snowfall |
|---|---|---|---|
| Max temp | · | · | · |
| Precip | -0.1077 | · | · |
| Snowfall | -0.3204 | 0.1248 | · |
| Snow depth | -0.2704 | 0.0312 | 0.4760 |

Notes: All weather variables are deviations from the 10-year baseline covering 1994-2003. Sample period is from 2004-2011.

Table 4: Effect of weather deviations on search intensity

| VARIABLES | (1) All Seasons | (2) Winter | (3) Spring | (4) Summer | (5) Fall |
|---|---|---|---|---|---|
| Max Temp, deg. C | -0.00240*** | -0.00656*** | -0.000740 | 0.00237* | -0.000445 |
| | (0.000641) | (0.00112) | (0.000892) | (0.00118) | (0.000896) |
| Precip., mm | -5.32e-05 | 0.00180* | 0.000196 | 0.00109* | -0.000232 |
| | (0.000472) | (0.000966) | (0.000856) | (0.000589) | (0.000919) |
| Snowfall, mm | -0.000433* | -0.000959*** | 0.000225 | 0.0641** | 0.000636 |
| | (0.000216) | (0.000235) | (0.000516) | (0.0310) | (0.000905) |
| Snow Depth, mm | -0.000176* | -0.000239** | -1.04e-05 | -1.85e-05 | -0.00116*** |
| | (9.22e-05) | (9.15e-05) | (0.000218) | (0.000199) | (0.000395) |
| Constant | 0.238*** | 0.228*** | 0.627*** | 0.935*** | 0.587*** |
| | (0.0154) | (0.0157) | (0.0126) | (0.0195) | (0.0161) |
| Observations | 16,546 | 4,269 | 4,320 | 3,485 | 4,472 |
| R-squared | 0.761 | 0.684 | 0.780 | 0.781 | 0.737 |

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered at the state level. All regressions also include year-month FE and state-month of year FE.

Table 5: Asymmetric effects of weather deviations on search intensity

| VARIABLES | (1) All Seasons | (2) All Seasons | (3) Winter | (4) Spring | (5) Summer | (6) Fall |
|---|---|---|---|---|---|---|
| Max Temp, deg. C | -0.00240*** | | | | | |
| | (0.000641) | | | | | |
| Pos dev, Max Temp, deg. C | | 0.00288*** | 0.00538*** | -0.00112 | 0.00704*** | 0.000795 |
| | | (0.000784) | (0.00154) | (0.00142) | (0.00164) | (0.00178) |
| Neg dev, Max Temp, deg. C | | 0.00805*** | 0.0163*** | -0.000269 | 0.00313 | 0.00238* |
| | | (0.00100) | (0.00171) | (0.00139) | (0.00191) | (0.00134) |
| Precip., mm | -5.32e-05 | | | | | |
| | (0.000472) | | | | | |
| Pos dev, Precip., mm | | 0.000570 | 0.00839*** | -0.000995 | 0.000216 | -0.000782 |
| | | (0.000739) | (0.00159) | (0.00133) | (0.000745) | (0.00111) |
| Neg dev, Precip., mm | | 0.00117 | 0.0103*** | -0.00320 | -0.00281** | -0.00162 |
| | | (0.00124) | (0.00243) | (0.00202) | (0.00138) | (0.00161) |
| Snowfall, mm | -0.000433* | | | | | |
| | (0.000216) | | | | | |
| Pos dev, Snowfall, mm | | 1.93e-05 | -0.000480 | 0.000215 | 0.0830** | 0.00128* |
| | | (0.000288) | (0.000295) | (0.000656) | (0.0370) | (0.000716) |
| Neg dev, Snowfall, mm | | 0.00286*** | 0.00259** | -0.000357 | 0.104 | 0.00758** |
| | | (0.000864) | (0.000989) | (0.00116) | (0.281) | (0.00318) |
| Snow Depth, mm | -0.000176* | | | | | |
| | (9.22e-05) | | | | | |
| Pos dev, Snow Depth, mm | | -6.65e-05 | -3.18e-05 | -0.000317 | 0.000309 | 0.000220 |
| | | (8.68e-05) | (9.44e-05) | (0.000190) | (0.000361) | (0.000560) |
| Neg dev, Snow Depth, mm | | 0.000452** | 0.000770*** | -0.000662 | 0.00459 | 0.00300** |
| | | (0.000203) | (0.000232) | (0.000596) | (0.00486) | (0.00125) |
| Constant | 0.238*** | 0.214*** | 0.162*** | 0.270*** | 0.908*** | 0.601*** |
| | (0.0154) | (0.0166) | (0.0187) | (0.0122) | (0.0205) | (0.0142) |
| Observations | 16,546 | 16,546 | 4,269 | 4,320 | 3,485 | 4,472 |
| R-squared | 0.761 | 0.763 | 0.696 | 0.781 | 0.783 | 0.741 |

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered at the state level. All regressions also include year-month FE and state-month of year FE.

Table 6: Persistence: Lag Coefficients by Season

| | Winter | | | Spring | | |
|---|---|---|---|---|---|---|
| | Max Temp | Precip | Snowfall | Max Temp | Precip | Snowfall |
| Pos dev: t | 0.00642*** | 0.00823*** | -0.000757** | -0.00111 | -0.000673 | -0.000509 |
| | (0.00177) | (0.00159) | (0.000330) | (0.00151) | (0.00132) | (0.000621) |
| Pos dev: t-1 | -0.00254* | 0.000386 | -0.00172*** | 0.00196 | -0.000574 | 0.000173 |
| | (0.00143) | (0.00168) | (0.000323) | (0.00132) | (0.000898) | (0.000774) |
| Pos dev: t-2 | -0.00310* | -0.00543*** | -0.000563 | 0.000194 | 0.000955 | -0.000735 |
| | (0.00165) | (0.00145) | (0.000391) | (0.00139) | (0.00160) | (0.000926) |
| Pos dev: t-3 | 0.00631*** | -0.00779*** | -0.000268 | -0.00127 | -0.000845 | 0.000737 |
| | (0.00116) | (0.00151) | (0.000318) | (0.00141) | (0.00123) | (0.000580) |
| Pos dev: t-4 | 0.00871*** | -0.00161 | 9.04e-05 | 0.00136 | 0.00159 | 0.00106** |
| | (0.00179) | (0.00134) | (0.000374) | (0.00100) | (0.00152) | (0.000473) |
| Neg dev: t | 0.0159*** | 0.00812*** | 0.00451*** | -0.00103 | -0.00219 | -0.00256 |
| | (0.00209) | (0.00258) | (0.00110) | (0.00152) | (0.00231) | (0.00200) |
| Neg dev: t-1 | 0.00851*** | -0.00422 | 0.00241** | 0.00248* | -0.000630 | -0.00230 |
| | (0.00167) | (0.00342) | (0.00100) | (0.00125) | (0.00185) | (0.00225) |
| Neg dev: t-2 | -0.00222 | -0.00764** | 0.00127 | -0.00214 | 0.00147 | -0.00155 |
| | (0.00166) | (0.00333) | (0.00121) | (0.00142) | (0.00275) | (0.00246) |
| Neg dev: t-3 | 0.000575 | -0.00145 | 0.00226 | -0.00102 | -0.00126 | 7.85e-05 |
| | (0.00183) | (0.00356) | (0.00151) | (0.00119) | (0.00318) | (0.00276) |
| Neg dev: t-4 | 0.00257* | 0.00150 | -0.000837 | 0.00160 | -0.00108 | 0.00141 |
| | (0.00135) | (0.00387) | (0.00110) | (0.00161) | (0.00272) | (0.00208) |
| p-val: sum pos coeffs | 0.000869 | 0.119 | 0.0233 | 0.775 | 0.901 | 0.691 |
| p-val: sum neg coeffs | 0.000376 | 0.749 | 0.0210 | 0.980 | 0.687 | 0.644 |
| | $R^2$=0.704; N=4211 | | | $R^2$=0.782; N=4320 | | |

| | Summer | | | Fall | | |
|---|---|---|---|---|---|---|
| | Max Temp | Precip | Snowfall | Max Temp | Precip | Snowfall |
| Pos dev: t | 0.00635*** | 9.79e-05 | 0.0513 | 0.00162 | -0.000944 | 0.000738 |
| | (0.00154) | (0.000718) | (0.0374) | (0.00177) | (0.00117) | (0.000612) |
| Pos dev: t-1 | 0.00494*** | 9.65e-05 | -0.00192 | 0.00170 | -0.00238*** | 0.000980 |
| | (0.000996) | (0.000963) | (0.00645) | (0.00154) | (0.000759) | (0.000771) |
| Pos dev: t-2 | 0.00310*** | -0.000868 | -0.000156 | 0.00727*** | -0.000436 | 0.00148 |
| | (0.000913) | (0.000746) | (0.00820) | (0.00210) | (0.000988) | (0.000988) |
| Pos dev: t-3 | 0.00126 | 0.00233*** | 0.00446 | 0.00596*** | -0.000659 | 0.000676 |
| | (0.00126) | (0.000701) | (0.00478) | (0.00182) | (0.000784) | (0.000817) |
| Pos dev: t-4 | 0.00167 | -5.42e-06 | 0.00856 | 0.000932 | 0.000236 | -0.000312 |
| | (0.00148) | (0.000800) | (0.00545) | (0.00211) | (0.000799) | (0.000900) |
| Neg dev: t | 0.00346* | -0.00170 | -0.269* | 0.00243* | -0.000769 | 0.0121*** |
| | (0.00192) | (0.00141) | (0.152) | (0.00132) | (0.00146) | (0.00246) |
| Neg dev: t-1 | 0.00227 | -0.00169 | 0.242 | 0.00202 | 0.00192 | 0.00590** |
| | (0.00165) | (0.00140) | (0.164) | (0.00132) | (0.00169) | (0.00278) |
| Neg dev: t-2 | 0.00381*** | 0.00188 | -0.0790 | 0.00492*** | 0.00244 | 0.0166*** |
| | (0.00125) | (0.00124) | (0.0753) | (0.00145) | (0.00209) | (0.00512) |
| Neg dev: t-3 | 0.000581 | -0.000334 | 0.215** | 4.25e-05 | -0.000244 | 0.00934 |
| | (0.00128) | (0.00147) | (0.0880) | (0.00124) | (0.00210) | (0.00749) |
| Neg dev: t-4 | -0.00240 | -0.000513 | 0.0302 | -0.00498*** | 0.000901 | -0.00299 |
| | (0.00161) | (0.00140) | (0.0384) | (0.00127) | (0.00212) | (0.0104) |
| p-val: sum pos coeffs | 2.22e-06 | 0.443 | 0.0934 | 0.00870 | 0.214 | 0.166 |
| p-val: sum neg coeffs | 0.0682 | 0.567 | 0.664 | 0.126 | 0.466 | 0.00232 |
| | $R^2$=0.793; N=3485 | | | $R^2$=0.750; N=4474 | | |

Notes: *** p<0.01, ** p<0.05, * p<0.1. Coefficients are from a single regression for each season. Standard errors are clustered at the state level. Regression also includes year-month FE and state-month of year FE. The p-values listed at the bottom of the table are for the F-test of the null hypothesis that the sum of the contemporaneous effect and all of the lags is equal to zero.

Table 7: Sensitivity to the Inclusion of Various Fixed Effects

| VARIABLES | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| Pos dev, Max Temp, deg. C | 0.00805** | 0.00909*** | 0.00376*** | 0.00288*** | 0.00477*** | 0.00362*** | 0.00225*** |
| | (0.00317) | (0.000856) | (0.000851) | (0.000784) | (0.000796) | (0.000683) | (0.000792) |
| Neg dev, Max Temp, deg. C | 0.0190*** | 0.0151*** | 0.0105*** | 0.00805*** | 0.00886*** | 0.00536*** | 0.00420*** |
| | (0.00293) | (0.00119) | (0.00107) | (0.00100) | (0.00113) | (0.00102) | (0.00112) |
| Pos dev, Precip., mm | -0.00225 | 0.00132 | 0.00130 | 0.000570 | 0.000541 | -0.000261 | -0.000860 |
| | (0.00309) | (0.000861) | (0.000843) | (0.000739) | (0.00107) | (0.000785) | (0.000844) |
| Neg dev, Precip., mm | -0.00482 | 0.00283* | 0.00198* | 0.00117 | 0.000943 | 0.000250 | -0.000849 |
| | (0.00615) | (0.00166) | (0.00115) | (0.00124) | (0.00127) | (0.00107) | (0.00116) |
| Pos dev, Snowfall, mm | -0.000132 | 0.00110*** | -0.000314 | 1.93e-05 | -0.000492 | -2.22e-05 | -2.20e-05 |
| | (0.000855) | (0.000301) | (0.000343) | (0.000288) | (0.000422) | (0.000362) | (0.000386) |
| Neg dev, Snowfall, mm | 0.0149*** | 0.00963*** | 0.00419*** | 0.00286*** | 0.00438*** | 0.00283*** | 0.00298*** |
| | (0.00385) | (0.00123) | (0.000826) | (0.000864) | (0.000855) | (0.000720) | (0.000850) |
| Pos dev, Snow Depth, mm | 0.000604*** | 4.61e-05 | -2.52e-05 | -6.65e-05 | 9.63e-05 | 9.00e-05 | 0.000125 |
| | (0.000200) | (9.12e-05) | (0.000102) | (8.68e-05) | (0.000124) | (0.000104) | (0.000108) |
| Neg dev, Snow Depth, mm | 0.00169*** | 0.000464** | 0.000441** | 0.000452** | 0.000552** | 0.000600** | 0.000644** |
| | (0.000391) | (0.000204) | (0.000201) | (0.000203) | (0.000247) | (0.000249) | (0.000245) |
| Constant | 0.340*** | 0.251*** | 0.260*** | 0.214*** | 0.162*** | 0.124*** | 0.128*** |
| | (0.0246) | (0.00936) | (0.00854) | (0.0166) | (0.00875) | (0.0180) | (0.0297) |
| Observations | 16,546 | 16,546 | 16,546 | 16,546 | 16,546 | 16,546 | 16,546 |
| R-squared | 0.072 | 0.597 | 0.695 | 0.763 | 0.737 | 0.811 | 0.837 |
| Year FE | - | X | X | - | X | - | - |
| Year-Month FE | - | - | - | X | - | X | - |
| Year-Week FE | - | - | - | - | - | - | X |
| State FE | - | X | - | - | - | - | - |
| State-MOY FE | - | - | X | X | - | - | - |
| State-WOY FE | - | - | - | - | X | X | X |

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered at the state level.

Table 8: Asymmetric effects of weather deviations: 25 Largest Cities

| VARIABLES | (1)<br>All Seasons | (2)<br>Winter | (3)<br>Spring | (4)<br>Summer | (5)<br>Fall |
|---|---|---|---|---|---|
| Pos dev, Max Temp, deg. C | 0.00477*** | 0.00598*** | 0.00187 | 0.00948*** | 0.00280** |
| | (0.000904) | (0.00170) | (0.00177) | (0.00223) | (0.00128) |
| Neg dev, Max Temp, deg. C | 0.00715*** | 0.0146*** | -0.00111 | 0.000826 | 0.00466*** |
| | (0.00106) | (0.00175) | (0.00160) | (0.00162) | (0.00153) |
| Pos dev, Precip., mm | -0.000145 | 0.000889 | -0.000809 | 0.000787 | 0.000558 |
| | (0.000527) | (0.00141) | (0.00115) | (0.000700) | (0.000634) |
| Neg dev, Precip., mm | 0.00214* | 0.00666*** | 0.000560 | 0.000118 | -0.000851 |
| | (0.00119) | (0.00176) | (0.00260) | (0.00156) | (0.00215) |
| Pos dev, Snowfall, mm | -0.000283 | -0.000140 | -0.000877** | -0.00220 | 0.000630* |
| | (0.000189) | (0.000247) | (0.000346) | (0.00490) | (0.000333) |
| Neg dev, Snowfall, mm | 0.00231** | 0.00197** | -0.000450 | 0.129 | 0.0191*** |
| | (0.000933) | (0.000885) | (0.00167) | (0.218) | (0.00652) |
| Pos dev, Snow Depth, mm | 3.00e-06 | -9.16e-05 | 4.72e-05 | 5.07e-05** | -1.98e-05 |
| | (5.10e-05) | (9.44e-05) | (4.05e-05) | (1.85e-05) | (0.000138) |
| Neg dev, Snow Depth, mm | 0.000259* | 0.000316** | 0.000212 | -8.67e-06 | -0.00135 |
| | (0.000139) | (0.000146) | (0.000213) | (0.000357) | (0.00144) |
| Constant | 0.176*** | 0.0943*** | 0.255*** | 0.257*** | 0.402*** |
| | (0.0125) | (0.0170) | (0.0247) | (0.0101) | (0.0159) |
| Observations | 8,868 | 2,201 | 2,248 | 2,072 | 2,347 |
| R-squared | 0.738 | 0.635 | 0.791 | 0.658 | 0.687 |

Notes: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Regression includes 25 largest metro areas, as grouped by Google: Atlanta, Baltimore, Boston, Chicago, Dallas/Fort Worth, Denver, Detroit, Houston, Los Angeles, Miami, Minneapolis/St. Paul, New York, Orlando, Philadelphia, Phoenix, Pittsburgh, Portland, Sacramento, San Antonio, San Diego, San Francisco, Seattle/Tacoma, St. Louis, Tampa, Washington (DC). Standard errors are clustered at the city level. All regressions also include year-month FE and city-month of year FE.

Table 9: Asymmetric effects of weather deviations, Farm states

| | | (1) All Seasons | (2) Winter | (3) Spring | (4) Summer | (5) Fall |
|---|---|---|---|---|---|---|
| Pos dev, Max Temp, deg. C | Farm states | 0.00178 | 0.00545 | -0.00102 | -0.000807 | -0.00119 |
| | | (0.00148) | (0.00348) | (0.00280) | (0.00380) | (0.00325) |
| | Non-farm states | 0.00325*** | 0.00491** | -0.00145 | 0.0102*** | 0.00206 |
| | | (0.000936) | (0.00185) | (0.00155) | (0.00132) | (0.00173) |
| Neg dev, Max Temp, deg. C | Farm states | 0.0115*** | 0.0208*** | 0.00481** | 0.00456 | 0.00338 |
| | | (0.00141) | (0.00280) | (0.00189) | (0.00375) | (0.00262) |
| | Non-farm states | 0.00557*** | 0.0130*** | -0.00345* | 0.00162 | 0.00212 |
| | | (0.00122) | (0.00188) | (0.00193) | (0.00177) | (0.00128) |
| Pos dev, Precip., mm | Farm states | -0.000915 | 0.00992*** | -0.000639 | -0.00129 | -0.00435 |
| | | (0.00206) | (0.00288) | (0.00292) | (0.00202) | (0.00319) |
| | Non-farm states | 0.00109 | 0.00792*** | -0.00108 | 0.000848 | 0.000271 |
| | | (0.000655) | (0.00196) | (0.00138) | (0.000606) | (0.000852) |
| Neg dev, Precip., mm | Farm states | 0.00382 | 0.00755* | 0.00683 | -0.00284 | -0.00156 |
| | | (0.00298) | (0.00440) | (0.00583) | (0.00363) | (0.00386) |
| | Non-farm states | 0.000240 | 0.0118*** | -0.00692*** | -0.00271* | -0.00193 |
| | | (0.00118) | (0.00293) | (0.00239) | (0.00143) | (0.00158) |
| Pos dev, Snowfall, mm | Farm states | -0.00117** | -0.00161*** | -0.00134** | 0.0671 | -0.00350* |
| | | (0.000469) | (0.000464) | (0.000548) | (0.0674) | (0.00185) |
| | Non-farm states | 0.000801** | 0.000242 | 0.00176*** | 0.0917* | 0.00300*** |
| | | (0.000302) | (0.000328) | (0.000635) | (0.0508) | (0.000761) |
| Neg dev, Snowfall, mm | Farm states | 0.00348 | 0.00342 | 0.000162 | 0.0542 | 0.00896** |
| | | (0.00291) | (0.00303) | (0.00262) | (0.404) | (0.00445) |
| | Non-farm states | 0.00232*** | 0.00237*** | -0.00103 | 0.173 | 0.00584 |
| | | (0.000622) | (0.000782) | (0.00141) | (0.363) | (0.00548) |
| Pos dev, Snow Depth, mm | Farm states | 6.12e-08 | 4.01e-05 | -0.000364* | 0.000223 | 0.000910 |
| | | (0.000152) | (0.000180) | (0.000185) | (0.000409) | (0.000859) |
| | Non-farm states | -0.000136 | -9.88e-05 | -0.000310 | -0.000319 | -0.000440 |
| | | (9.22e-05) | (7.49e-05) | (0.000284) | (0.000736) | (0.000508) |
| Neg dev, Snow Depth, mm | Farm states | 0.000260* | 0.000767** | -0.00158*** | 0.00555 | 0.00233*** |
| | | (0.000131) | (0.000352) | (0.000566) | (0.00544) | (0.000784) |
| | Non-farm states | 0.000590** | 0.000792** | -4.57e-05 | -0.0138 | 0.00338 |
| | | (0.000269) | (0.000323) | (0.000349) | (0.0144) | (0.00272) |
| Constant | | 0.215*** | 0.161*** | 0.726*** | 0.907*** | 0.597*** |
| | | (0.0186) | (0.0231) | (0.0132) | (0.0286) | (0.0138) |
| Observations | | 16,546 | 4,269 | 4,320 | 3,485 | 4,472 |
| R-squared | | 0.764 | 0.697 | 0.784 | 0.785 | 0.742 |

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered at the state level. All regressions also include year-month FE and state-month of year FE. Farm states are defined as those for which farming accounts for more than 1% of GSP on average in our sample years: AL, AR, IA, ID, KS, KY, MN, MS, MT, ND, NE, NM, OK, OR, SD, VT, WA, and WI.

Table 10: Asymmetric effects of weather deviations, Ski states

| | | (1)<br>All Seasons | (2)<br>Winter | (3)<br>Spring | (4)<br>Summer | (5)<br>Fall |
|---|---|---|---|---|---|---|
| Pos dev, Max Temp, deg. C | Ski states | 0.00474*** | 0.0114*** | -0.000795 | 0.00392 | 0.00319 |
| | | (0.00105) | (0.00420) | (0.00178) | (0.00526) | (0.00330) |
| | Non-ski states | 0.00227** | 0.00407** | -0.00168 | 0.00810*** | -0.000152 |
| | | (0.00104) | (0.00172) | (0.00186) | (0.00147) | (0.00196) |
| Neg dev, Max Temp, deg. C | Ski states | 0.0119*** | 0.0256*** | 0.00419 | 0.000336 | 0.00113 |
| | | (0.00233) | (0.00480) | (0.00369) | (0.00446) | (0.00199) |
| | Non-ski states | 0.00656*** | 0.0131*** | -0.00162 | 0.00406** | 0.00282* |
| | | (0.00103) | (0.00148) | (0.00176) | (0.00199) | (0.00163) |
| Pos dev, Precip., mm | Ski states | 0.000874 | 0.00838* | -0.00302 | 0.000937 | 0.000704 |
| | | (0.00103) | (0.00493) | (0.00317) | (0.00142) | (0.00234) |
| | Non-ski states | 0.000526 | 0.00875*** | -0.000871 | -5.11e-05 | -0.00126 |
| | | (0.000866) | (0.00162) | (0.00148) | (0.000875) | (0.00115) |
| Neg dev, Precip., mm | Ski states | 0.00127 | 0.00913** | 0.00553 | -0.00813*** | -0.00514 |
| | | (0.00304) | (0.00416) | (0.00480) | (0.00266) | (0.00564) |
| | Non-ski states | 0.00102 | 0.0103*** | -0.00534** | -0.00192 | -0.000735 |
| | | (0.00133) | (0.00288) | (0.00255) | (0.00155) | (0.00146) |
| Pos dev, Snowfall, mm | Ski states | -0.000257 | -0.000851 | 0.00101 | 0.0798** | 0.00209* |
| | | (0.000543) | (0.000683) | (0.000688) | (0.0393) | (0.00116) |
| | Non-ski states | 0.000126 | -0.000351 | -4.20e-05 | 0.135 | 0.000806 |
| | | (0.000388) | (0.000351) | (0.000857) | (0.0945) | (0.00143) |
| Neg dev, Snowfall, mm | Ski states | 0.00200 | 0.00120 | -0.000463 | 0.222 | 0.00260 |
| | | (0.00145) | (0.00186) | (0.00146) | (0.392) | (0.00443) |
| | Non-ski states | 0.00487*** | 0.00565*** | -0.00204 | -0.0143 | 0.0115*** |
| | | (0.000687) | (0.000906) | (0.00219) | (0.249) | (0.00390) |
| Pos dev, Snow Depth, mm | Ski states | -5.59e-05 | -0.000104 | -4.21e-05 | 0.000474 | -9.02e-05 |
| | | (0.000135) | (0.000168) | (0.000173) | (0.000498) | (0.000548) |
| | Non-ski states | -0.000111 | -4.22e-05 | -0.000704*** | 0.000228 | 0.000532 |
| | | (9.06e-05) | (7.00e-05) | (0.000153) | (0.000304) | (0.00113) |
| Neg dev, Snow Depth, mm | Ski states | 0.000582*** | 0.000927*** | -0.000503 | 0.00530 | 0.00419** |
| | | (0.000187) | (0.000188) | (0.000600) | (0.00601) | (0.00159) |
| | Non-ski states | -0.000249 | -0.000331 | -6.09e-05 | 0.000959 | 0.00196 |
| | | (0.000243) | (0.000279) | (0.000752) | (0.00640) | (0.00167) |
| Constant | | 0.218*** | 0.168*** | 0.578*** | 0.900*** | 0.599*** |
| | | (0.0170) | (0.0191) | (0.0150) | (0.0212) | (0.0144) |
| Observations | | 16,546 | 4,269 | 4,320 | 3,485 | 4,472 |
| R-squared | | 0.764 | 0.699 | 0.783 | 0.783 | 0.741 |

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered at the state level. All regressions also include year-month FE and state-month of year FE. Ski states are defined as those in the top quartile in terms of number of ski areas in 2010-11: CA, CO, ID, ME, MI, MN, MT, NH, NY, PA, VT, WA, and WI.

Table 11: Asymmetric effects of weather deviations, Green states

| | | (1) All Seasons | (2) Winter | (3) Spring | (4) Summer | (5) Fall |
|---|---|---|---|---|---|---|
| Pos dev, Max Temp, deg. C | Green states | 0.00764*** | 0.0135*** | -0.00150 | 0.00846** | 0.00771*** |
| | | (0.00117) | (0.00409) | (0.00241) | (0.00419) | (0.00266) |
| | Non-green states | 0.00206** | 0.00237 | -0.00163 | 0.00754*** | -0.00129 |
| | | (0.00100) | (0.00150) | (0.00188) | (0.00140) | (0.00191) |
| Neg dev, Max Temp, deg. C | Green states | 0.0102*** | 0.0235*** | 0.00405 | -0.000506 | -0.00490** |
| | | (0.00292) | (0.00548) | (0.00477) | (0.00457) | (0.00197) |
| | Non-green states | 0.0107*** | 0.0192*** | 0.00356** | 0.00383* | 0.00263 |
| | | (0.00116) | (0.00176) | (0.00149) | (0.00220) | (0.00174) |
| Pos dev, Precip., mm | Green states | 0.00294*** | 0.0119*** | -0.00117 | 0.00203*** | 0.000244 |
| | | (0.000893) | (0.00279) | (0.00193) | (0.000693) | (0.00126) |
| | Non-green states | 6.80e-05 | 0.00975*** | -0.000692 | -0.000883 | -0.00133 |
| | | (0.00127) | (0.00281) | (0.00199) | (0.00107) | (0.00176) |
| Neg dev, Precip., mm | Green states | 0.00223 | 0.0114*** | -0.000125 | -0.00686*** | -0.00586 |
| | | (0.00218) | (0.00386) | (0.00385) | (0.00211) | (0.00374) |
| | Non-green states | 0.00204 | 0.00909*** | -0.00444* | -0.00120 | 0.00260 |
| | | (0.00140) | (0.00321) | (0.00248) | (0.00181) | (0.00198) |
| Pos dev, Snowfall, mm | Green states | 0.000159 | -5.41e-05 | 0.00212*** | 0.228*** | 0.000872 |
| | | (0.000455) | (0.000536) | (0.000610) | (0.0399) | (0.00118) |
| | Non-green states | -0.000707 | -0.000525 | -0.000976 | 0.0274 | -0.000746 |
| | | (0.000511) | (0.000458) | (0.000883) | (0.0338) | (0.00161) |
| Neg dev, Snowfall, mm | Green states | 0.00275*** | 0.00281* | -0.00128 | 2.000*** | -0.000699 |
| | | (0.000929) | (0.00154) | (0.00129) | (0.382) | (0.00754) |
| | Non-green states | 0.00607*** | 0.00635*** | 0.00157 | -0.214*** | 0.0122*** |
| | | (0.00146) | (0.00169) | (0.00214) | (0.0680) | (0.00339) |
| Pos dev, Snow Depth, mm | Green states | -2.91e-05 | 2.90e-05 | -0.000399** | -0.000120 | 0.000983 |
| | | (0.000140) | (0.000166) | (0.000185) | (0.000514) | (0.000828) |
| | Non-green states | -2.84e-05 | -8.13e-05 | -0.000294 | 8.94e-05 | -0.000168 |
| | | (0.000145) | (0.000119) | (0.000289) | (0.000413) | (0.000634) |
| Neg dev, Snow Depth, mm | Green states | 0.000503** | 0.00117*** | -0.000811 | 0.00198 | 0.00516 |
| | | (0.000219) | (0.000157) | (0.000634) | (0.00540) | (0.00324) |
| | Non-green states | 0.000316 | 0.000234 | 0.000910** | -0.00385 | 0.00263** |
| | | (0.000314) | (0.000296) | (0.000421) | (0.0105) | (0.00118) |
| Constant | | 0.265*** | 0.222*** | 0.705*** | 0.437*** | 0.654*** |
| | | (0.00907) | (0.0158) | (0.0106) | (0.0158) | (0.0119) |
| Observations | | 16,546 | 4,269 | 4,320 | 3,485 | 4,472 |
| R-squared | | 0.695 | 0.633 | 0.767 | 0.776 | 0.715 |

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered at the state level. All regressions also include year-month FE and state-month of year FE. Green states are defined as those in the top quartile in terms of the average LCV rating of House delegations during 2004-2011: CT, DE, HI, MA, MD, ME, NH, NJ, NY, OR, RI, VT, WA. DC is also considered to be a green state.

Table 12: Environmental Votes, Local Weather and Search Intensity

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Pos Dev, Max Temp | -0.000127 | 0.000251 | -0.00129 | | | |
| | (0.00140) | (0.00138) | (0.00137) | | | |
| Neg Dev, Max Temp | -0.00443*** | -0.00577*** | -0.00259* | | | |
| | (0.00153) | (0.00154) | (0.00151) | | | |
| Pos Dev, Snowfall | -0.000332 | -0.0000782 | -0.000241 | | | |
| | (0.000440) | (0.000453) | (0.000320) | | | |
| Neg Dev, Snowfall | 0.00431*** | 0.00332*** | 0.00198* | | | |
| | (0.000993) | (0.000984) | (0.00115) | | | |
| Climate Change Search Intensity | | | | 0.297*** | 0.240*** | 0.0858** |
| | | | | (0.0381) | (0.0376) | (0.0398) |
| Observations | 62092 | 62092 | 62092 | 62053 | 62053 | 62053 |
| R-Squared | 0.656 | 0.659 | 0.673 | 0.656 | 0.659 | 0.673 |

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered at the state * vote level.

Table 13: ACU Votes, Local Weather and Search Intensity

| | All Non-environment Votes | | | Same-week Non-environment Votes | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Climate Change Search Intensity | -0.0222 | -0.00633 | 0.0545 | 0.0330 | -0.00854 | 0.00535 |
| | (0.0365) | (0.0367) | (0.0413) | (0.0524) | (0.0537) | (0.0530) |
| Observations | 90143 | 90143 | 90143 | 41509 | 41509 | 41509 |
| R-Squared | 0.551 | 0.554 | 0.569 | 0.542 | 0.549 | 0.573 |

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered at the state * vote level.

Table 14: Environmental Votes and Search Intensity, by Representative Characteristics

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Climate Change Search Intensity | 0.140** | 0.0792 | -0.0959 | | | |
| | (0.0700) | (0.0697) | (0.0671) | | | |
| Senate * Search Intensity | -0.0941* | -0.111** | -0.0210 | -0.143*** | -0.162*** | -0.0677 |
| | (0.0504) | (0.0503) | (0.0487) | (0.0507) | (0.0505) | (0.0487) |
| Democrat * Search Intensity | 0.292*** | 0.304*** | 0.310*** | | | |
| | (0.0752) | (0.0755) | (0.0750) | | | |
| LCV rating 00% * Search Intensity | | | | 0.159** | 0.0691 | -0.104 |
| | | | | (0.0656) | (0.0666) | (0.0669) |
| LCV rating 10% * Search Intensity | | | | 0.303** | 0.282** | 0.127 |
| | | | | (0.129) | (0.128) | (0.122) |
| LCV rating 20% * Search Intensity | | | | 0.371** | 0.313* | 0.128 |
| | | | | (0.182) | (0.180) | (0.172) |
| LCV rating 30% * Search Intensity | | | | 0.0744 | 0.0204 | -0.118 |
| | | | | (0.251) | (0.250) | (0.241) |
| LCV rating 40% * Search Intensity | | | | 0.0674 | 0.0879 | -0.103 |
| | | | | (0.329) | (0.323) | (0.314) |
| LCV rating 50% * Search Intensity | | | | 1.311*** | 1.224*** | 1.102*** |
| | | | | (0.325) | (0.319) | (0.306) |
| LCV rating 60% * Search Intensity | | | | 0.906*** | 0.852*** | 0.633*** |
| | | | | (0.198) | (0.195) | (0.187) |
| LCV rating 70% * Search Intensity | | | | 0.853*** | 0.821*** | 0.608*** |
| | | | | (0.177) | (0.174) | (0.167) |
| LCV rating 80% * Search Intensity | | | | 0.718*** | 0.663*** | 0.478*** |
| | | | | (0.102) | (0.0993) | (0.0978) |
| LCV rating 90% * Search Intensity | | | | 0.186*** | 0.136*** | -0.00583 |
| | | | | (0.0261) | (0.0280) | (0.0389) |
| Observations | 62053 | 62053 | 62053 | 62053 | 62053 | 62053 |
| R-Squared | 0.656 | 0.659 | 0.673 | 0.657 | 0.660 | 0.674 |

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered at the state * vote level.

## Appendix: Robustness to missing data

As noted earlier in the paper, the algorithm that Google Insights uses to distribute data publicly induces a censoring problem. There is no suitable instrument that varies at the week-state level that we could use for an exclusion restriction in a selection model. Hence, we carefully analyze the patterns of missing observations and rerun our main specification on several subsamples. First, Figure A1 shows year-by-year maps depicting the number of weeks of missing data in each of the lower 48 states. After the first couple of lower search volume years, the missing observations are largely confined to the northern Rocky Mountain states (which are sparsely populated). The most severe case is Wyoming, which never appears in our sample.

In Table A1, we restrict our sample to state-years in which there are no missing observations. That is, this sample consists only of the state-years on the maps that appear in the lightest shade of red. For conveniences, the corresponding columns from Table 5 are interspersed: these are the columns in which "Full sample" is labeled "Y". The results are broadly similar; the main exception is that the effect of an unusually warm winter week is no longer significant. However, the effect of unusually little snow remains.

In Table A2, we construct a balanced panel for the years 2007-2011. We determined that this set of years gave us the best balance between panel length (5 years) and inclusion of states (32). The set of states covers a broad swath of the country, both politically and geographically. The columns in which the panel is unbalanced are the full sample from 2007-2011 to facilitate comparison. Again, the results of the balanced panel analysis are broadly comparable to those with the unbalanced panels, whether the unbalanced sample starts in 2004 or 2007.

Figure A1: Missing observations, 2004-2007

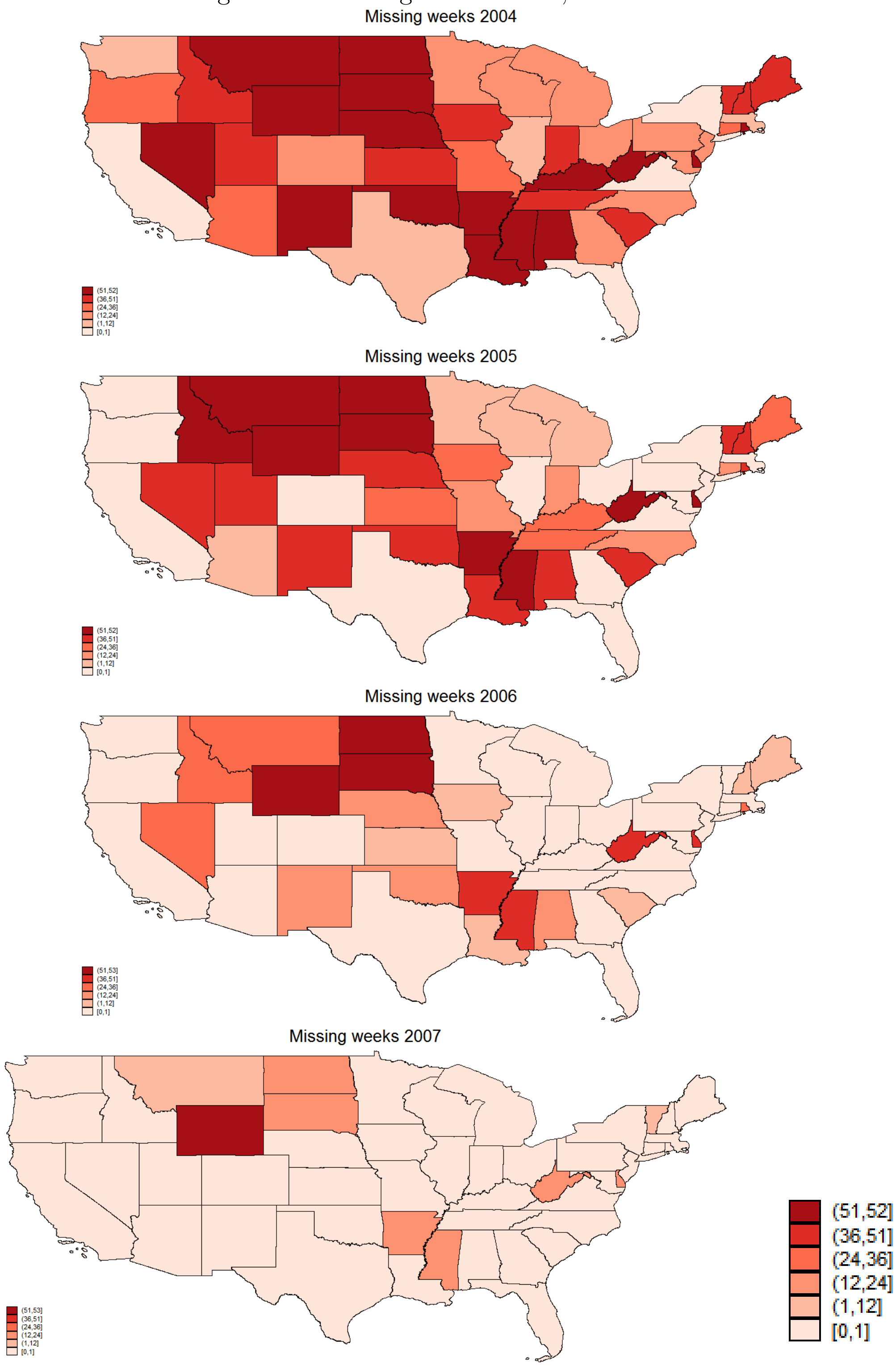

Figure A2: Missing observations, 2008-2011

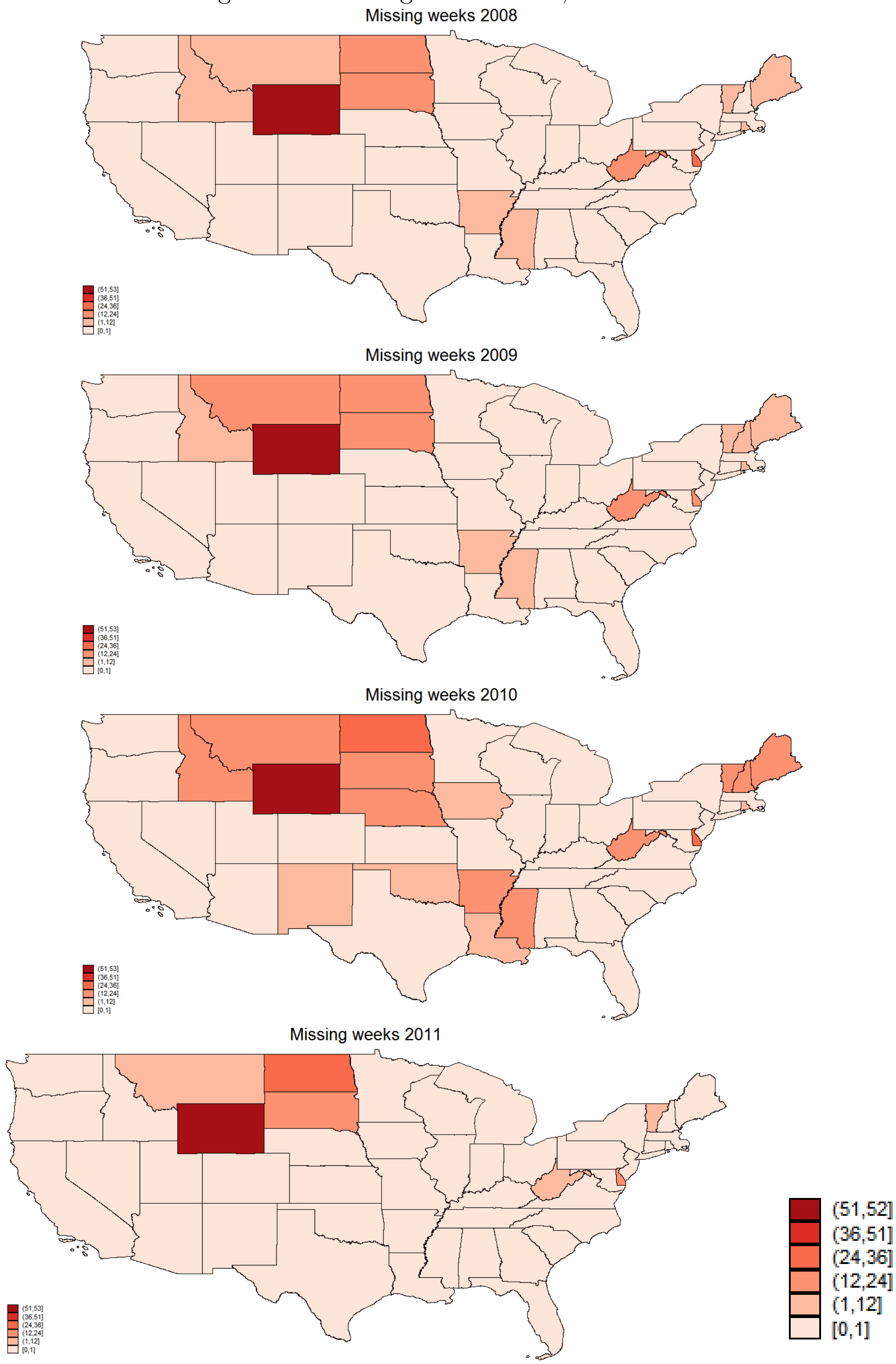

Table A1: Robustness to Missing Data

| VARIABLES | (1) indexCC | (2) All Seasons | (3) Winter | (4) Winter | (5) Spring | (6) Spring | (7) Summer | (8) Summer | (9) Fall | (10) Fall |
|---|---|---|---|---|---|---|---|---|---|---|
| Pos dev, Max Temp, deg. C | 0.00288*** | 0.00263*** | 0.00538*** | 0.00219 | -0.00112 | 0.000434 | 0.00704*** | 0.00724*** | 0.000795 | 0.00175 |
| | (0.000784) | (0.000872) | (0.00154) | (0.00161) | (0.00142) | (0.00157) | (0.00164) | (0.00126) | (0.00178) | (0.00147) |
| Neg dev, Max Temp, deg. C | 0.00805*** | 0.00792*** | 0.0163*** | 0.0147*** | -0.000269 | 0.000759 | 0.00313 | 0.00253* | 0.00238* | 0.00449*** |
| | (0.00100) | (0.000976) | (0.00171) | (0.00162) | (0.00139) | (0.00136) | (0.00191) | (0.00143) | (0.00134) | (0.00141) |
| Pos dev, Precip., mm | 0.000570 | 0.00128* | 0.00839*** | 0.00890*** | -0.000995 | -0.000324 | 0.000216 | 0.000636 | -0.000782 | 0.000221 |
| | (0.000739) | (0.000740) | (0.00159) | (0.00199) | (0.00133) | (0.00124) | (0.000745) | (0.000811) | (0.00111) | (0.00105) |
| Neg dev, Precip., mm | 0.00117 | 0.00288** | 0.0103*** | 0.0141*** | -0.00320 | -0.00231 | -0.00281** | -0.00239* | -0.00162 | -0.000438 |
| | (0.00124) | (0.00122) | (0.00243) | (0.00292) | (0.00202) | (0.00199) | (0.00138) | (0.00138) | (0.00161) | (0.00134) |
| Pos dev, Snowfall, mm | 1.93e-05 | 0.000827*** | -0.000480 | 0.000223 | 0.000215 | 0.00116 | 0.0830** | 0.0883** | 0.00128* | 0.00120 |
| | (0.000288) | (0.000197) | (0.000295) | (0.000230) | (0.000656) | (0.000733) | (0.0370) | (0.0415) | (0.000716) | (0.000832) |
| Neg dev, Snowfall, mm | 0.00286*** | 0.00342*** | 0.00259** | 0.00336*** | -0.000357 | 0.000509 | 0.104 | 0.209 | 0.00758** | 0.00506 |
| | (0.000864) | (0.000869) | (0.000989) | (0.000976) | (0.00116) | (0.00146) | (0.281) | (0.322) | (0.00318) | (0.00480) |
| Pos dev, Snow Depth, mm | -6.65e-05 | -0.000147* | -3.18e-05 | -0.000124 | -0.000317 | -0.000360 | 0.000309 | -0.000326 | 0.000220 | 0.000482 |
| | (8.68e-05) | (8.09e-05) | (9.44e-05) | (8.29e-05) | (0.000190) | (0.000267) | (0.000361) | (0.000200) | (0.000560) | (0.000502) |
| Neg dev, Snow Depth, mm | 0.000452** | 0.000657* | 0.000770*** | 0.000772* | -0.000662 | -5.23e-05 | 0.00459 | 0.000350 | 0.00300** | 0.00477* |
| | (0.000203) | (0.000351) | (0.000232) | (0.000414) | (0.000596) | (0.000224) | (0.00486) | (0.00150) | (0.00125) | (0.00246) |
| Constant | 0.214*** | 0.176*** | 0.162*** | 0.125*** | 0.270*** | 0.406*** | 0.908*** | 1.064*** | 0.601*** | 1.363*** |
| | (0.0166) | (0.0169) | (0.0187) | (0.0279) | (0.0122) | (0.0282) | (0.0205) | (0.00884) | (0.0142) | (0.0478) |
| Observations | 16,546 | 12,302 | 4,269 | 3,025 | 4,320 | 3,105 | 3,485 | 3,106 | 4,472 | 3,066 |
| R-squared | 0.763 | 0.791 | 0.696 | 0.720 | 0.781 | 0.816 | 0.783 | 0.776 | 0.741 | 0.762 |
| Full Sample | Y | N | Y | N | Y | N | Y | N | Y | N |

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered at the state level. Columns for which the full sample is not used include only year-state combinations for which there are no missing observations.

Table A2: Robustness to Balanced Panel 2007-2011

| VARIABLES | (1) All Seasons | (2) All Seasons | (3) Winter | (4) Winter | (5) Spring | (6) Spring | (7) Summer | (8) Summer | (9) Fall | (10) Fall |
|---|---|---|---|---|---|---|---|---|---|---|
| Pos dev, Max Temp, deg. C | 0.00279*** | 0.00244** | 0.00632*** | 0.00254 | -0.000875 | 0.000190 | 0.00579*** | 0.00722*** | 9.21e-05 | 0.000839 |
| | (0.000878) | (0.00104) | (0.00198) | (0.00184) | (0.00182) | (0.00180) | (0.00195) | (0.00159) | (0.00187) | (0.00152) |
| Neg dev, Max Temp, deg. C | 0.00895*** | 0.00755*** | 0.0182*** | 0.0146*** | -0.00138 | -0.00169 | 0.00253 | 0.00343* | 0.00320* | 0.00535*** |
| | (0.00115) | (0.00101) | (0.00201) | (0.00145) | (0.00179) | (0.00177) | (0.00200) | (0.00181) | (0.00186) | (0.00150) |
| Pos dev, Precip., mm | 0.000456 | 0.00198** | 0.0114*** | 0.0101*** | -0.00224 | 0.000672 | -4.91e-05 | 0.000970 | -0.00196 | -0.000119 |
| | (0.00104) | (0.000841) | (0.00192) | (0.00211) | (0.00176) | (0.00131) | (0.000957) | (0.000877) | (0.00158) | (0.00107) |
| Neg dev, Precip., mm | 0.000999 | 0.00271* | 0.0139*** | 0.0146*** | -0.00564** | -0.00424* | -0.00247 | -0.000918 | -0.00408 | -0.00154 |
| | (0.00161) | (0.00152) | (0.00305) | (0.00347) | (0.00240) | (0.00227) | (0.00188) | (0.00190) | (0.00245) | (0.00148) |
| Pos dev, Snowfall, mm | -4.39e-05 | 0.000542** | -0.000556 | -0.000105 | 5.79e-05 | 0.000540 | 0.0832** | 0.0994** | 0.000906 | 0.00162** |
| | (0.000324) | (0.000214) | (0.000355) | (0.000303) | (0.000743) | (0.000474) | (0.0379) | (0.0444) | (0.000744) | (0.000682) |
| Neg dev, Snowfall, mm | 0.00174 | 0.00273*** | 0.000763 | 0.00225** | -0.000223 | -0.000472 | 0.122 | 0.0262 | 0.00658* | 0.00722* |
| | (0.00166) | (0.000977) | (0.00185) | (0.00110) | (0.00117) | (0.00158) | (0.302) | (0.174) | (0.00386) | (0.00384) |
| Pos dev, Snow Depth, mm | -6.25e-05 | -0.000140 | -2.59e-05 | -0.000144 | -0.000249 | -0.000141 | 0.000500 | -0.000371** | -4.64e-05 | -0.000127 |
| | (7.71e-05) | (9.90e-05) | (9.45e-05) | (9.64e-05) | (0.000183) | (0.000263) | (0.000584) | (0.000153) | (0.000567) | (0.000320) |
| Neg dev, Snow Depth, mm | 0.000259 | 0.000121 | 0.000731** | 9.13e-05 | -0.00122 | 7.50e-05 | 0.0252 | 0.0118*** | 0.00185 | 0.00341*** |
| | (0.000387) | (0.000193) | (0.000321) | (0.000197) | (0.000842) | (0.000250) | (0.0154) | (0.00336) | (0.00167) | (0.00114) |
| Constant | 0.655*** | 0.158*** | 0.284*** | 0.525*** | 0.899*** | 0.870*** | 0.904*** | 0.173*** | 0.690*** | 0.442*** |
| | (0.0145) | (0.0104) | (0.0185) | (0.0179) | (0.0186) | (0.0135) | (0.0156) | (0.00520) | (0.0140) | (0.0104) |
| Observations | 12,179 | 8,270 | 3,112 | 2,007 | 3,207 | 2,099 | 2,701 | 2,099 | 3,159 | 2,065 |
| R-squared | 0.761 | 0.786 | 0.670 | 0.672 | 0.767 | 0.811 | 0.762 | 0.690 | 0.749 | 0.758 |
| Balanced panel | N | Y | N | Y | N | Y | N | Y | N | Y |

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered at the state level. Columns with a balanced panel are a balanced panel for of states that are not missing any observations from 2007-2011: AL, AZ, CA, CO, CT, DC, FL, GA, HI, IL, IN, KS, KY, MA, MD, MI, MN, MO, NC, NJ, NV, NY, OH, OR, PA, SC, TN, TX, UT, VA, WA, WI. Columns without a balanced panel include all observations from 2007-2011.

## Appendix: Weather coefficients by month

Table A3: Regressions by Month

| VARIABLES | (1) Jan | (2) Feb | (3) Mar | (4) Apr | (5) May | (6) Jun | (7) Jul | (8) Aug | (9) Sep | (10) Oct | (11) Nov | (12) Dec |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Max Temp: Pos | 0.00279 | 0.00690*** | -0.00109 | -0.00157 | 0.000609 | 0.00660** | 0.00920*** | 0.00410 | 0.00840** | -0.00312 | -0.000163 | 0.00646** |
| | (0.00225) | (0.00223) | (0.00317) | (0.00219) | (0.00278) | (0.00253) | (0.00219) | (0.00268) | (0.00325) | (0.00261) | (0.00227) | (0.00307) |
| Max Temp: Neg | 0.0123*** | 0.0127*** | -0.00124 | -0.00487** | 0.00519 | -0.00390 | 0.00572** | 0.00544*** | 0.00101 | -0.00309* | 0.0129*** | 0.0240*** |
| | (0.00237) | (0.00264) | (0.00229) | (0.00218) | (0.00361) | (0.00426) | (0.00227) | (0.00195) | (0.00227) | (0.00159) | (0.00402) | (0.00271) |
| Precip: Pos | 0.000552 | 0.00631* | -0.000723 | -0.00585 | 0.00187 | 0.00289* | -0.000795 | -0.000538 | 3.08e-05 | -0.000376 | -0.000339 | 0.0130*** |
| | (0.00238) | (0.00333) | (0.00158) | (0.00366) | (0.00190) | (0.00167) | (0.000912) | (0.00119) | (0.00108) | (0.00187) | (0.00217) | (0.00249) |
| Precip: Neg | 0.00611* | 0.00544 | -0.00349 | -0.00374 | -0.00287 | -0.00632** | -0.00179 | 0.00189 | -0.000744 | 0.00120 | -0.00775** | 0.0131*** |
| | (0.00362) | (0.00385) | (0.00356) | (0.00489) | (0.00382) | (0.00247) | (0.00235) | (0.00262) | (0.00247) | (0.00321) | (0.00322) | (0.00388) |
| Snowfall: Pos | -0.000890* | 8.69e-06 | -0.000344 | 0.00111 | 0.0117*** | 0.0976** | -0.0737 | 4.620** | 0.0792 | -0.00114 | -0.000723 | 0.000757 |
| | (0.000476) | (0.000380) | (0.000895) | (0.00175) | (0.00332) | (0.0386) | (0.652) | (2.070) | (0.0553) | (0.00231) | (0.00110) | (0.000750) |
| Snowfall: Neg | -0.000481 | 0.00427** | -0.000136 | -0.00530 | 0.0319* | 0.117 | -2.256*** | 1.859*** | 0.0133 | 0.00997 | 0.00859** | 0.00582*** |
| | (0.00152) | (0.00196) | (0.00116) | (0.00397) | (0.0173) | (0.269) | (0.785) | (0.422) | (0.0255) | (0.00746) | (0.00363) | (0.00211) |
| Snow Depth: Pos | 0.000335*** | 8.23e-05 | -0.000329* | -7.47e-05 | -0.000362 | 8.74e-05 | 0.000564** | 0.00199*** | -0.0559 | 0.00304 | -0.000341 | -0.000809*** |
| | (9.58e-05) | (9.20e-05) | (0.000184) | (0.000446) | (0.000352) | (0.000481) | (0.000261) | (0.000485) | (0.0406) | (0.00209) | (0.000518) | (0.000291) |
| Snow Depth: Neg | 0.00124*** | 0.000563** | -0.000474 | -0.00184 | -0.00145 | 0.00576 | -0.00870*** | 0.0236*** | 0.0806*** | 0.00329*** | 0.00286* | 0.000383 |
| | (0.000384) | (0.000224) | (0.000430) | (0.00134) | (0.00210) | (0.00518) | (0.00137) | (0.00270) | (0.00684) | (0.000760) | (0.00145) | (0.000347) |
| Constant | 0.192*** | 0.271*** | 0.267*** | 0.346*** | 0.167*** | 0.184*** | 0.153*** | 0.233*** | 0.242*** | 0.285*** | 0.341*** | 0.165*** |
| | (0.0211) | (0.0157) | (0.0147) | (0.0132) | (0.0167) | (0.0169) | (0.0145) | (0.0172) | (0.0111) | (0.0160) | (0.0159) | (0.0249) |
| Observations | 1,419 | 1,349 | 1,423 | 1,448 | 1,449 | 1,122 | 1,178 | 1,185 | 1,346 | 1,594 | 1,532 | 1,501 |
| R-squared | 0.726 | 0.775 | 0.785 | 0.791 | 0.739 | 0.761 | 0.820 | 0.769 | 0.749 | 0.772 | 0.699 | 0.630 |

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered at the state level. All regressions include state and year FE.

# Appendix: Significance of differences in effects - Farm, Ski and Green States

Table A4: Significance of differences in effects: Farming states

| | All Seasons | Winter | Spring | Summer | Fall |
|---|---|---|---|---|---|
| Max Temp: Pos | -0.00146 | 0.000541 | 0.000422 | -0.0111** | -0.00324 |
| Max Temp: Neg | 0.00593*** | 0.00784** | 0.00826*** | 0.00294 | 0.00126 |
| Precip: Pos | -0.002 | 0.002 | 0.000438 | -0.00214 | -0.00462 |
| Precip: Neg | 0.00358 | -0.00424 | 0.0137** | -0.000131 | 0.000370 |
| Snowfall: Pos | -0.00197*** | -0.00186*** | -0.00310*** | -0.0246 | -0.00650*** |
| Snowfall: Neg | 0.00116 | 0.00105 | 0.00119 | -0.119 | 0.00312 |
| Snow Depth: Pos | 1.36E-04 | 1.39E-04 | -5.36E-05 | 5.42E-04 | 0.00135 |
| Snow Depth: Neg | -0.00033 | -0.0000252 | -0.00153** | 0.0194 | -0.00105 |

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered at the state level. Table entries are the difference between coefficients for farming states and non-farming states.

Table A5: Significance of differences in effects: Skiing states

| | All Seasons | Winter | Spring | Summer | Fall |
|---|---|---|---|---|---|
| Max Temp: Pos | 0.00248 | 0.00730 | 0.000890 | -0.00418 | 0.00334 |
| Max Temp: Neg | 0.00533** | 0.0126** | 0.00581 | -0.00372 | -0.00168 |
| Precip: Pos | 0.000348 | -0.000368 | -0.00215 | 0.000988 | 0.00197 |
| Precip: Neg | 0.000246 | -0.00122 | 0.0109* | -0.00621** | -0.00440 |
| Snowfall: Pos | -0.000383 | -0.000500 | 0.00105 | -0.0549 | 0.00128 |
| Snowfall: Neg | -0.00287* | -0.00445** | 0.00157 | 0.236 | -0.00894 |
| Snow Depth: Pos | 5.47e-05 | -6.18e-05 | 0.000662*** | 0.000247 | -0.000622 |
| Snow Depth: Neg | 0.000831*** | 0.00126*** | -0.000442 | 0.00434 | 0.00223 |

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered at the state level. Table entries are the difference between coefficients for skiing states and non-skiing states.

Table A6: Significance of differences in effects: Green states

| | All Seasons | Winter | Spring | Summer | Fall |
|---|---|---|---|---|---|
| Max Temp: Pos | 0.00561*** | 0.0103** | 0.00118 | 0.00144 | 0.00901*** |
| Max Temp: Neg | 0.00105 | 0.00908 | 0.000245 | -0.00421 | -0.00494** |
| Precip: Pos | 0.00118 | 0.00374 | -0.00299 | 0.00259* | 0.00233 |
| Precip: Neg | -0.000112 | -0.00326 | 0.00263 | -0.00345 | -0.000995 |
| Snowfall: Pos | 0.000232 | -2.94e-05 | 0.00180* | 0.196*** | -3.69e-05 |
| Snowfall: Neg | -0.00273 | -0.00253 | -0.00319 | 2.196*** | -0.00908 |
| Snow Depth: Pos | 0.000136 | 0.000214 | -3.92e-05 | -0.000312 | 0.00165* |
| Snow Depth: Neg | 0.000422 | 0.00108*** | -0.00145* | 0.00808 | 0.00248 |

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered at the state level. Table entries are the difference between coefficients for green states and non-green states.