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The Impact of Weather on Local Employment: Using Big Data on Small Places

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Abstract

This paper exploits vast granular data – over 10 million county-industry-month observations – to estimate dynamic panel data models of weather's short-run employment effects. I estimated the contemporaneous and cumulative effects of temperature, precipitation, snowfall, the frequency of very hot days, the frequency of very cold days, and natural disasters on private nonfarm employment growth. The short-run effects of weather vary considerably across sectors and regions. Favorable weather in one county has positive spillovers to nearby counties but negative spillovers to distant counties. Local climate mediates weather effects: economies are less sensitive to types of weather they are accustomed to.

JEL Codes: Q52, Q54, R11

Keywords: Weather, climate, local employment growth, local economic shocks

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I. Introduction

It is readily apparent that weather can have large short-run effects on economic activity, and in some industries more than others. Indeed, unusual weather is routinely cited as a factor in explaining unexpected fluctuations in macroeconomic data. Yet, the existing literature provides a surprisingly sparse understanding of weather's short-run impact on overall economic activity. With a few exceptions, prior research has tended to focus on either the long-run economic effects of climate change[1] or the short-run effects of weather on the agriculture and energy sectors.[2]

By contrast, this paper exploits the availability of vast granular local data on employment and weather to provide an in-depth understanding of weather's local employment effects. Specifically, I combine BLS monthly administrative-record data from January 1980 to December 2015 on employment by county and industry with daily NOAA weather-station data. County weather measures are constructed using spatial interpolation based on inverse-distance from points within the county to nearby weather stations. The resulting county-month-industry panel data set on employment and weather consists of over 10 million observations.

I use these data to estimate dynamic panel data (DPD) models of weather's local employment effects. This paper builds on recent work by Bloesch and Gourio (2015), who estimate a state level DPD model of employment growth (and other economic outcomes) in winter months as a function of temperature and snowfall, and Boldin and Wright, who estimate a national dynamic time series model

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[1] For example, Dell, Jones, and Olken (2012) estimate the effects of climate change on national incomes and economic growth. Similarly, Deryugina and Hsiang (2014) investigate the effect of temperature on annual income, but at the U.S. county level. See Dell, Jones, and Olken (2014) for a survey of the literature on the economic effects of climate change. See Severin, Costello, and Deschenes (2016) for an assessment of the effects of climate change on agricultural land values. Lastly, see Auffhammer and Mansur (2014) for a survey of studies investigating the effects of weather and climate change on energy consumption.

[2] See, for example, Deschenes and Greenstone (2007). There is also a large literature on the impacts of weather or climate on non-economic outcomes such as crime (e.g., Ranson 2013) and mortality (e.g., Deschenes and Moretti (2009) or Deschenes and Greenstone (2011)). See also Graff Zivin and Neidell (2014), which studies the effects of temperature on time use using county panel data.

of employment growth as a function of temperature, snowfall, and precipitation. [3,4] It also builds on the work by Deschenes and Greenstone (2011) and Severen, Costello, and Deschenes (2016), which use county-level data to study the effects of weather on agricultural production and farm land values at an annual frequency (in addition to considering the effects of projected climate change on these outcomes).

The combination of high-frequency and finely geographically-disaggregated data used in this paper offers considerable advantages. First, one can estimate weather effects far more precisely than has been done previously. Second, one can estimate very rich specifications. In particular, one can allow for numerous weather variables; for lagged effects (to assess mean reversion and the permanence of weather effects); for heterogeneity in weather effects across key dimensions such as region, season, and industry; and for nonlinear effects. Third, one can precisely test various hypotheses related to the economy's sensitivity to weather. For instance, in this paper, I investigate the extent to which local economies adapt to their climate and to changes in their climate.

The vastness of the data set also allows one to control for high-dimensional fixed effects. The models estimated in the paper are estimated separately by industry and include fixed effects for county*calendar-month*decade (to control for county-by-industry-by-decade seasonal patterns in employment growth) and time (sample-month) fixed effects (to control for industry-specific national common factors such as business cycles, oil price shocks, etc.).

The estimates from these models reveal a number of interesting, and in some cases surprising,

[3] Boldin and Wright (2015) estimate a mixed-frequency time series model of weather's effects on national employment growth, simultaneously estimating seasonal factors. They use the monthly BLS Current Employment Statistics data along with daily national measures of temperature, precipitation, heating degree days (HDD) and the Regional Snowfall Index (RSI). (See description of RSI in Section II below.) National measures of temperature, precipitation, and HDD are obtained by averaging the readings from weather stations in the 50 largest MSAs and then calculating the deviation of that weather variable from its calendar-day average over the prior 30 years. Bloesch and Gourio (2015) constructs similar measures of weather deviations, but at the state-level, and estimates a state dynamic panel data model for employment growth and other economic outcomes, focusing just on winter months. Both papers use their estimated models to weather-adjust national employment data using a similar methodology to that described in Section VI.

[4] See also Colacito, Hoffmann, and Phan (2014), which estimates an annual state panel model of the contemporaneous relationship between GDP growth and temperature by season. Similarly, Lazo, et al. (2011) uses an annual state panel model to estimate the contemporaneous effects of temperature and precipitation on GDP growth.

findings. First, I find that local monthly employment growth in the U.S. is increasing in the average temperature for the month. This contemporaneous boost from temperature occurs in all seasons, but it is especially strong in the spring. The initial employment boost from temperature, however, is largely transitory: negative effects of lagged temperature lead to near-zero cumulative effects over a four month period. Interestingly, this pattern for local employment growth within the U.S. concords with cross-country evidence from Dell, el al. (2014) that finds a near-zero effect of temperature on economic growth at an annual frequency for richer countries, though they find a negative and significant effect among poorer countries.[5]

Second, precipitation and snowfall have clear negative contemporaneous effects. Precipitation's effect is offset by higher growth in the subsequent three months, while snowfall's four-month cumulative effect remains negative. Third, I find that the frequency of very hot days (temperatures over 90°F or 32.2°C) in a month, holding average temperature fixed, has a negative contemporaneous and cumulative effect on employment growth. By contrast, I find no contemporaneous or cumulative effect on employment growth from the frequency of very cold days (below 30°F or -1.1°C).

I find that the effects of weather differ considerably across industries and regions. The most weather-sensitive industries generally are Construction, Mining and Logging, Leisure and Hospitality, Retail Trade, and Manufacturing. The results across regions often are consistent with the notion that regions accustomed to certain inclement weather conditions are less sensitive to deviations in those weather variables. For instance, the negative effect per unit of snowfall is largest in the South Atlantic and East South Central – two of the three regions with the lowest average snowfall.

I perform several additional exercises to more fully explore the economic effects of weather. First, I estimate the employment effects of natural disasters, such as floods, tornados, hurricanes, and

[5] See also Burke, Hsiang, and Miguel (2015) which finds that countries' per capita income falls with temperature at an annual frequency.

earthquakes. Disasters negatively affect employment in that month, but boost employment cumulatively over at least four months. The longer the duration of the disaster, the bigger the impacts. Industry-level results reveal the post-disaster-month boost to employment is concentrated in Construction, Mining & Logging, Retail Trade, and Professional and Business Services, suggesting that the boost is likely due to rebuilding and repair activity. The cumulative positive effect of disasters in local employment effects contrasts somewhat with other research on the economic effects of natural disasters, which has found negative effects on income growth at an annual frequency (e.g., Strobl 2011 and Noy 2009).

Second, the extent to which weather in other counties has spillover effects on employment growth in a given focal county is investigated using spatial lag models. In general, I find that weather in nearby counties has effects on the focal county's employment growth of the same sign but smaller magnitude as the effects of own-county weather. However, weather in far-away counties tends to have opposite effects from those of own-county weather, suggesting that local economies compete to some extent with distant local economies, with unfavorable weather putting local economies at least temporarily at a disadvantage.

Finally, I consider the issue of adaptation, which is of critical relevance to the economics of climate change (Kahn (2015) and Deschênes and Greenstone (2011)). I investigate two distinct aspects of adaptation. The first aspect focuses on the cross-sectional variation and evaluates the extent to which a locality's climate (i.e., average weather) mediates the effect of weather deviations on employment growth. For instance, is the adverse effect of snow larger in places unaccustomed to it than in places with snowy climates? Or is the positive effect of temperature increases in the spring greater in places that typically experience cold temperatures in the spring compared with places used to having warm springs? I find the answer is yes. Specifically, the negative effects of snowfall and precipitation on employment growth and the positive effect of temperature on employment growth in the spring are each attenuated when the respective weather variable is interacted with its county-specific mean over the sample period (1990-2015).

A second aspect relates to adaptation over time within locality and whether the effects of weather have changed over time. Specifically, I extend the baseline regression model to include interactions of each weather variables (and its lags) with a second-half-of-the-sample indicator. The impact of weather could well have increased or decreased over time. On the one hand, technological advances such as air conditioning, solar and hydroelectric generation, and snow removal equipment and chemicals may have made local economies more resilient to weather shocks. On the other hand, many local climates have shifted in recent decades and if localities have been slow to adapt, their economies may well have become more sensitive to weather shocks. The results are mixed. The positive contemporaneous effects of temperature on employment growth in the spring and fall have increased modestly over time, inconsistent with the technological adaptation hypothesis. Yet, the negative contemporaneous effect of snowfall is significantly lower in the second half of the sample, suggesting that local economies have become much more resilient to snow-related disruptions over time.

The remainder of the paper is organized as follows. The next section describes the data on employment and weather. I then lay out in Section III the baseline empirical model for estimating the effects of weather on local employment growth. The baseline results are presented in Section IV, while results on non-linear effects and the effects of disasters are presented in Section V. In Section VI, I assess the nature of spatial spillovers from local weather. Section VII explores the issue of adaptation of local economies to their climate and to changes in their climate. Finally, in Section VIII, I discuss the potential mechanisms underlying weather's economic effects and the extent to which the empirical results confirm these mechanisms. Section IX concludes.

II. Data

A. Employment and Other Outcomes

Data on employment by county, industry, and month are available from the Quarterly Census of Employment and Wages (QCEW).[6] As of the time of this writing, the QCEW data for NAICS industries are available from January 1990 through December 2015. Data for SIC industries is available from January 1975 through December 2000. The QCEW is compiled by the Bureau of Labor Statistics based on state Unemployment Insurance administrative records. Nearly all private nonfarm employers in the U.S. are required to report monthly employment counts and quarterly total wages of their employees to their state's Unemployment Insurance agency. Employment covers "all full- and part-time workers who worked during or received pay (subject to Unemployment Insurance wages) for the pay period which includes the 12th day of the month."[7] Note that this is the same definition of employment used in the payroll survey underlying the widely-followed national monthly employment report (i.e., the BLS Current Employment Statistics (CES) report).[8]

The CES payroll survey does not cover agriculture, ranching, fishing, and hunting, which are included in the QCEW's all-industry employment total. Thus, to ensure full comparability between the CES and QCEW industry coverage, I construct an alternative QCEW "all-industry" sample that excludes these subsectors (which are a very small fraction of QCEW total employment).

B. Weather

Measures of monthly weather at the county level were constructed from the Global Historical Climatology Network Daily (GHCN-Daily) data set. The GHCN-Daily is provided by the U.S. National Climatic Data Center (part of the National Oceanic and Atmospheric Administration (NOAA)) and contains daily weather measurements from weather stations throughout the United

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[6] http://www.bls.gov/cew/datatoc.htm.
[7] http://www.bls.gov/cew/cewproper.htm.
[8] http://www.bls.gov/web/empsit/cesfaq.htm#qc2.

States and around the world.[9] The number of weather stations varies over time, averaging around 1,200. There is entry and exit of weather stations. All weather stations available at a given point in time are used for measuring county weather at that point in time. **Appendix Figure 1** shows the location of the weather stations operating as of January 1, 2006. The spatial distribution of weather stations is highly correlated with the spatial distribution of population.

Following Ranson (2014), these records from individual weather stations are used to estimate county-level weather using an inverse-distance weighting procedure. First, the surface of the conterminous United States is divided into a 5-mile by 5-mile grid. Second, weather values for each grid point are estimated using inverse-distance-weighted averages of the weather values from weather stations within 50 miles of the grid point. As an illustration, **Appendix Figure 2** shows the 50-mile radius around the center of Atlanta, Georgia. The green dots show the location of weather stations. While there are no weather stations in the county (Fulton) containing Atlanta, there are nine stations within 50 miles. For each weather variable, this procedure measures weather for the center of Atlanta using a weighted average of the weather values from these nine stations, weighting stations by the inverse of their distance from the center.

These county level *daily* weather measures are then used to construct the following *monthly* weather variables: mean daily high temperature, fraction of days in the month in which the maximum temperature was above 90˚ Fahrenheit (F), fraction of days in which the minimum temperature was below 30˚ F, mean daily precipitation, and mean daily snowfall.

These measures of weather over calendar month are the primary weather variables used in this paper. However, I also construct measures of weather over the first 12 days of the month and over the 30 days ending with the 12th of the month because similar measures have been used in prior work, notably Boldin and Wright (2015). The logic of using pre-12th weather stems from the fact that BLS

[9] http://www.ncdc.noaa.gov/oa/climate/ghcn-daily/.

employment data (both CES payroll survey and QCEW counts) are meant to measure the number of individuals on employer payrolls as of the pay period containing the 12^{th} of the month. Consequently, weather during pay periods that start after the 12^{th} of the month should be irrelevant to measured employment in that month. In particular, for employees paid on a semimonthly frequency, which means their pay periods are the first half of the month and the second half of the month, only weather in the first half of the month should matter.

However, according to the BLS (Burgess 2014), only 20% of private businesses have semimonthly pay periods and this percentage goes down sharply with size class, so that far less than 20% of employment is covered by semimonthly pay periods. The most common (35% of businesses and a much higher share of employment) frequency of pay is biweekly, where the two-week period containing the 12th can range from the 14 days ending with the 12^{th} to the 14 days starting with the 12^{th} to any 14-day interval in between. Thus, it is not clear that weather during just the first 12 days of the month is more relevant, and it could well be less relevant, for measured monthly employment growth than weather for the full calendar month. Nonetheless, I also have estimated the baseline models described below using weather measured either over the first 12 days of the month or over the 30 days prior to the 12^{th} of the month in order to assess the sensitivity of the baseline results to this timing. The results are similar using these alternative measures, though the fitted models based on these measures yield somewhat lower power for predicting national employment surprises.

I augment these weather-station based data with county-level data on major storms and other disasters from the Federal Emergency Management Authority (FEMA).[10] This database contains information on the county, start date, end date, and disaster type for all FEMA disaster declarations from 1953 to present. From these data, I construct two county-month indicator variables, one

[10] The data are available at https://www.fema.gov/openfema-dataset-disaster-declarations-summaries-v1. I include only disaster observations classified as "Major Disasters" by FEMA.

indicating whether there was a disaster covering part of the month and one indicating whether there was a disaster covering the entire month.[11]

III. Estimating Local Weather Effects – Methodology

A. Specification

I estimate weather's economic effects using the following dynamic panel data (DPD) model (and variants of it):

$$\Delta l_{cst} = \gamma_{st} + \alpha_{c,s,m(t),d(t)} + \sum_{k=1}^{K}\sum_{j=1}^{9}\sum_{i=1}^{4}\sum_{p=1}^{10}\sum_{\tau=0}^{3}\beta_{jip\tau}^{k}\cdot 1[c\in R_j]\cdot 1[t\in S_i]\cdot 1[s=p]\cdot w_{c,t-\tau}^{k} + \epsilon_{cst} \quad (1)$$

where Δl_{cst} is the change in log non-seasonally-adjusted nonfarm employment in county c, industry s, and month t. γ_{st} is an industry-specific time (month of sample) fixed effect, which absorbs all industry-specific national common factors such as business cycles, oil price shocks, foreign economic shocks, monetary policy changes, and federal fiscal or regulatory policy changes. $\alpha_{c,s,m(t),d(t)}$ is a county- and industry-specific calendar-month*decade fixed effect. The inclusion of this fixed effect has the effect of seasonally adjusting employment growth, where seasonal patterns are specific to each county-industry pair and are allowed to vary by decade. This type of seasonal adjustment via calendar-month fixed effects (for each county-industry-decade) is done partly because the BLS does not provide seasonally-adjusted QCEW data at the county level. However, even if they did, there is a statistical advantage to estimating this seasonality jointly with the weather effects: As demonstrated in Boldin and Wright (2015), seasonal adjustment factors may be biased if they are estimated in a model that does not account for weather because of the correlation between time-varying seasonal factors and recent weather.

[11] I also used data on storm damages from the NOAA Storm Events Database, which provides estimates of monetary damages (crop and property damages) for major storm events by county and month. Storm damages were found to have very little effect on employment growth, except in the Construction sector, and so were omitted from the baseline empirical model.

The $\beta^k_{jip\tau}$ are the key parameters to be estimated. They capture the effect of each weather variable, by industry, by season, and by region, on employment growth in the current month and up to three months ahead. $1[t \in R_j]$ is an indicator equal to 1 if county c is in region R_j; $1[t \in S_i]$ is an indicator variable equal to 1 if month t is in season S_i; $1[s = p]$ is a set of 10 indicator variables for industries; and $w^k_{c,t-\tau}$ is one of K weather variables for the month $t - \tau$. Seasons are defined as follows: Winter = {December, January, February}; Spring = {March, April, May}; Summer = {June, July, August}; and Fall = {September, October, December}. The regions are the nine Census Bureau regions (see **Appendix Figure 3**). The baseline model includes six (monthly) weather variables: average daily precipitation (millimeters), average daily snowfall (centimeters), average daily high temperature (degrees Fahrenheit), the fraction of days in which the low temperature is below 30°F (-1.1°C), and the fraction of days in which the high temperature is above 90°F (32.2°C).

Weather is likely to have quite heterogeneous effects across industries. For instance, below-freezing days are likely to have adverse effects on the construction industry, but positive effects on utilities. Thus, I allow for full heterogeneity across industries by estimating the model separately for each major industry and for private all-industry.[12] The industries are defined by the QCEW supersector classifications, which are aggregates of NAICS two-digit industries.[13]

The model is estimated using weighted OLS, where the weights are log county employment. The weighting is done to mitigate the influence of sparsely populated counties. Measurement error in the weather data is likely to be inversely proportional to population given that less populous counties generally have fewer or no weather stations and thus the weather data for these counties relies more heavily on spatial interpolation. In addition, to mitigate the influence of measurement error and outliers in the dependent variable, I winsorize employment growth at the 1st and 99th percentiles (i.e.,

[12] Pooling data across industries would allow for seemingly unrelated regression, which would increase efficiency. However, the pooled estimation is computational intensive; hence, thus far, I have estimated the model separately for each industry.
[13] See http://www.bls.gov/cew/supersector.htm for QCEW supersector classifications.

values below the 1st and above the 99th percentiles are replaced with the 1st and 99th percentile values, respectively). Lastly, employment is not reported for some industry*county*month cells due to BLS disclosure restrictions; this generally occurs only for narrow industries in sparsely populated counties. For each industry, I restrict the sample of counties to those with a complete time series on employment.

B. Constraints

Without constraints imposed, the above model yields 7,200 $\hat{\beta}^k_{jip\tau}$ parameter estimates.[14] To reduce this number while retaining the economically important sources of heterogeneity in weather effects, I consider imposing some reasonable constraints. First, as noted above, I allow for full heterogeneity across industries by estimating the DPD model separately by industry. However, for the purposes of illustrating other sources of heterogeneity, I also estimate the model on total (all-industry) private-sector employment growth, which in effect imposes a constraint of no industry heterogeneity.

Second, note that there is already in equation (1) a constraint imposed by the number of lags included in the model. The model assumes that lags beyond 3 months have no effect, which is supported by a Wald test involving comparing the baseline model to a model with 4 lags. However, there are no constraints imposed on the lag structure within that lag length. This allows for the possibility of permanent (or at least persistent) weather effects and transitory (mean-reverting) weather effects.

Third, I consider constraints on season heterogeneity. Temperature seems likely to have different effects in the summer – when, for example, hotter temperatures may have adverse effects on retail and leisure activity – than in the winter – when warmer days may well boost retail and leisure. Yet, a reasonable (and testable) constraint on the model might be to assume the other weather variables – snow, fraction of days below 30°F, fraction of days above 90°F, and precipitation – have

[14] 5 weather variables X 9 regions X 4 seasons X 10 industries X 4 lags.

approximately the same marginal effects on employment growth throughout the year.[15] Hence, I impose this joint constraint and test the constraint via a Wald test.

A priori, regional heterogeneity in weather effects seems important and it is largely absent from previous studies.[16] Weather is inherently a local phenomenon and its primary economic impacts are felt locally; national average effects may be of limited value. On the other hand, allowing for full regional heterogeneity complicates the ability to succinctly characterize the effects of weather and could also lead to overfitting. Hence, I estimate two versions of the DPD model: one version with full regional heterogeneity, as in equation (1), and one version without regional heterogeneity – that is, with each $\hat{\beta}^k_{jip\tau}$ assumed to be equal across regions ($\hat{\beta}^k_{jip\tau} = \hat{\beta}^k_{ip\tau}$). The much more parsimonious no-regional-heterogeneity model is especially useful for characterizing the patterns of industry heterogeneity and for testing alternative specifications such as those considered in Section V.

IV. Estimating Local Weather Effects – Baseline Results

A. Model Without Regional Heterogeneity

Even with the constraints on season heterogeneity, the model in equation (1) still yields several thousand estimates of weather effects. In this subsection, I present the key parameter estimates and their statistical significance in a variety of tables and figures. Statistical significance is based on

[15] Note that this constraint on marginal effects (β^k) does not preclude these weather variables from having different predicted total effects ($\beta^k w^k_{cst}$) across seasons. For instance, though the effects of one centimeter of snowfall is assumed to be the same in all seasons, snowfall will typically be zero in summer months for most counties and hence will typically have no predicted effect on employment growth in those county-months while its predicted effect in winter months will typically be non-zero due to positive snowfall.

[16] Neither Boldin and Wright (2015) nor Bloesch and Gourio (2014) *explicitly* allow for regional heterogeneity in weather effects, however they do measure aggregate weather based on deviations-from-normal-weather at the city (Boldin and Wright) or state (Bloesch and Gourio) levels. Thus, the underlying assumption is *not* that all places respond the same to an inch of snow or an extra degree of temperature, but that all places respond the same to an inch of snow above *their* average or an extra degree of temperature above *their* average. It should also be noted that Boldin and Wright, in some specifications, include the Regional Snowfall Index (RSI) provided by the National Centers for Environmental Information (NCEI)(see Squires et al. 2014), which incorporates some regional heterogeneity in snowfall effects. The RSI rates snowstorms based on their "societal impact," where the latter is based on the severity of the storm, its spatial extent, and its nexus with population centers. However, the index only covers storms in the eastern two-thirds of the United States and only covers the subset of storms NCEI considers "major" (roughly 5 per year).

standard errors that are robust to heteroskedasticity and allow for two-way clustering of the residuals. The first cluster group is county. Clustering by county allows for any form of within-county serial correlation. The second cluster group is state*sample-month, which allows for cross-sectional spatial correlation across counties within a state.[17] Allowing for this cross-sectional spatial correlation accounts for both the natural spatial correlation of weather across local areas but also any correlation introduced by the fact that neighboring counties may use data from the same weather station(s) in the process of constructing the weather variables for their county.

Each weather regressor is normalized by its full-sample standard deviation so that the coefficient magnitudes can be compared across the different weather variables. Each coefficient represents the effect on local employment growth of a one standard deviation change in that weather measure. These standard deviations are shown in **Table 1**, which also shows the means, minimum values, and maximum values for all variables used in the analysis. The top panel shows these summary statistics for the full sample, while the lower four panels show them by season.

The regression results are presented in a manner so as to illustrate the key sources of heterogeneity in weather effects: across weather variables, across time lags, across regions, across seasons, and across industries. To most succinctly characterize the effects across the first four of these five dimensions, I start by presenting estimates from the model where the dependent variable is private-sector all-industry employment growth – that is, a model without industry heterogeneity. Furthermore, to illustrate the average dynamic patterns of weather effects, I start with the version of the model without regional heterogeneity (i.e., constraining coefficients to be the same across regions).

The coefficients and standard errors from estimating equation (1) for private all-industry employment growth without regional heterogeneity are shown in **Table 2**. Recall that the standard

[17] Recall that the regressions are estimated separately by industry, so in effect the cluster groups are really county*industry and state*sample-month*industry.

errors are robust to heteroskedasticity and two-way clustering by county and by state*sample-month. The regression uses a balanced panel of 960,372 observations from 3,108 counties. The panel covers 309 months from January 1990 to December 2015.[18] The first column of the table shows the estimated coefficients (and their standard errors) on the contemporaneous values of the weather variables. The second, third, and fourth columns show the coefficients and standard errors for the one-, two-, and three-month lagged values, respectively. The implied four-month cumulative effect is provided in the final column. These results are also presented graphically in **Figure 1**, where each bar represents a coefficient estimate. The eight weather variables (with temperature separated by season) are indicated on the horizontal axis. The number of months by which the variable is lagged is indicated on the depth axis.

I find that higher temperatures have a positive and statistically significant contemporaneous effect on employment growth in all four seasons. The effects are economically significant as well. For instance, in spring months, a one standard deviation (18.1°F) increase in average daily-high temperature is associated with 0.12 percentage point higher employment growth in the same month. Note that average monthly employment growth in the sample is 0.08 percentage point (see **Table 1**), so this spring temperature effect represents a more than doubling relative to baseline employment growth.[19] Temperature has much larger contemporaneous effects on employment growth in the spring than in other months, with an effect twice as large as the effects in the summer or winter and nearly five times the effect in the fall.

Precipitation and snowfall have modest negative contemporaneous effects; both are

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[18] The results are similar using a longer sample from January 1980 to December 2015. I present results here using the 1990+ sample so that the all-industry results can be compared to the industry-specific results. Employment data by NAICS industries is unavailable prior to 1990.

[19] To put this in perspective, note that 0.12p.p. of monthly employment growth is equivalent to 1.45p.p. at an annual rate. Also, note that the average daily-high temperature variable used in the regressions is units of standard deviations, where the standard deviation is computed over the full sample (all seasons). As shown in **Table 1**, the full sample standard deviation is 18.1°F; the standard deviation computed over only spring months is 12.0°F. Hence, an increase in average daily-high temperature equal to one standard deviation of *spring* temperature would increase contemporaneous employment growth by a smaller amount, roughly 0.08p.p.

significant at below the 1% level. The coefficient of -0.023 on precipitation implies that a month with one standard deviation higher than normal rainfall, equivalent to roughly 58 centimeters or 2.3 inches, experiences -0.023 percentage point lower employment growth. Similarly, a month with one standard deviation (about 15 centimeters or 6 inches) higher than normal snowfall is associated with -0.020 percentage point lower employment growth. Put differently, given that average monthly employment growth is 0.08 percentage point, it would take about 2 feet of snowfall to entirely offset typical employment growth for the month.

The fraction of days in the month in which the high temperature exceeded 90°F and the fraction of days in which the low temperature fell below 30°F, holding constant the average daily high temperature over the month, each have negative point estimates, though the effect of days below 30°F is not statistically significant.

The lagged effects of weather generally are of opposite sign to the contemporaneous effect and largest for the first two lags.[20] Over the course of four months, the implied cumulative effects tend to be close to zero and statistically insignificant. However, there are two noteworthy exceptions. First, I find there is little if any rebound in employment growth following snowfall's significant contemporaneous effect, so that snowfall has a negative cumulative effect. Second, I find that the fraction of days above 90°F has a negative effect on employment growth in the current month and up to 3 months later, leading to a sizable negative cumulative effect. Though it is difficult to know the mechanisms underlying such effects, one possible explanation for this last effect is that very hot days increase business operating costs (e.g., air conditioning) which, if persistent over several months, can significantly dampen employment growth.

To illustrate the industry heterogeneity in weather effects, I estimate this same model (again constraining coefficients to be constant across regions) separately for each industry (QCEW

[20] This result is consistent with Bloesch and Gourio (2015), who estimate a state-level DPD model for winter employment growth and similarly find that, first, temperature has a positive contemporaneous effect but negative lagged effects and, second, that snowfall has a negative contemporaneous effect but positive lagged effects.

supersector). The full set of results for each industry are shown in **Appendix Tables 1-11**. To summarize these results, I plot the contemporaneous weather coefficients across industries in the heatmap shown in **Figure 2**. The implied four-month cumulative effects are shown in **Figure 3**. In each heatmap, positive coefficients are depicted by blue circles while negative coefficients are depicted by red circles, with darker shading for larger absolute values. The statistical significance of the coefficients is indicated by stars, with one, two, and three stars indicating significance at the 10%, 5%, and 1% levels, respectively.

Figure 2 shows that the most weather-sensitive industries generally are Construction, Mining and Logging, Leisure and Hospitality, Retail Trade, and Manufacturing. In terms of temperature, the positive contemporaneous effect of temperature (mean daily high) found above for all-industry employment growth is especially strong for employment growth in these industries as well as in Transportation and Warehousing, Manufacturing, and Professional and Business Services. However, the strength of the temperature effect in each industry varies by season. For most industries, Spring temperature appears to be particularly important, consistent with the all-industry results.

For Construction, while temperature is found to have significant effects on employment growth throughout the year, the coefficients on contemporaneous temperature are much larger for the Winter and Spring. In **Appendix A**, I take a more in-depth look at weather's impacts on the construction sector. There I show that the effects of weather on construction employment turn out to vary substantially across regions. I also compare those effects to the estimated effects of weather on local building permits, data for which is also available at the county-by-month level. In general, the effects of weather on building permits are very similar to the effects on construction employment growth.

Precipitation and snowfall have negative and significant contemporaneous effects in many industries. The number of very hot days has a highly significant negative effect on employment growth in Leisure and Hospitality, while the number of very cold days has a significant negative effect in that industry as well as in Construction and in Retail Trade. These effects on Leisure and Hospitality are not surprising given how much the industry relies on vacationing and outdoor recreational activities, the demand for which is greatly reduced by extreme temperatures. It is also consistent with the results of Graff Zivin and Neidell (2014). They use county panel data on temperatures and time use and find, *inter alia*, that temperature increases, especially at the lower end of the temperature range, lead to more outdoor recreation. The results for Retail Trade are consistent with those of Tran (2016), who estimated the local weather effects on individual store retail sales for a national apparel and sporting goods brand. Tran found that retail sales generally increased with daily temperature but, similar to Graff Zivin and Neidell, the effect was especially pronounced at the low (below-freezing) end of the temperature range.

Figure 3 shows an analogous heatmap for the four-month cumulative effects of each weather variable on each industry's employment growth. The cumulative effect of each weather variable is calculated by summing the coefficients on the contemporaneous and lagged values of that variable. Relative to the contemporaneous effects, the cumulative effects tend to be smaller in magnitude and less statistically significant, suggesting that in general lagged weather effects – "bouncebacks" or "paybacks" – tend to offset contemporaneous weather effects. There are some notable exceptions. As we found for all-industry employment growth, temperature has a large negative cumulative effect on summer employment growth in Mining and Logging and in Construction, though it has a modest positive cumulative effect in the Information industry. I also find that the negative cumulative effect of the frequency of very hot days appears to be quite broad-based across industries. Again, this is consistent with the possibility that very hot days add to business operating costs in all industries. Similarly, snowfall tends to have a negative cumulative effect, but it is only statistically significant in Mining and Logging and in Construction. The number of very cold days also has a significant negative cumulative effect in Construction. Lastly, precipitation is found to have a positive cumulative effect in Construction and, to a lesser extent, in Retail Trade and in Information, but it has a negative cumulative effect in Mining and Logging and in Manufacturing.

B. Model With Regional Heterogeneity

To illustrate the heterogeneity of weather effects *across regions*, I return to the estimates of the model allowing for regional heterogeneity (equation (1)) and produce similar heatmaps depicting the effects of each weather variable on all-industry employment growth in each of the nine Census Bureau regions. **Figure 4** shows the heatmap for the contemporaneous effects, while **Figure 5** shows the heatmap for the four-month cumulative effects.

Starting with **Figure 4**, the positive and significant contemporaneous temperature effects in the spring and winter found earlier are found to be broad-based across regions, though they tend to be largest in the Pacific region. Interestingly, the contemporaneous effect of the number of very hot days, which is negative, also is found to be largest in the Pacific region. The contemporaneous effect of precipitation is fairly broad-based, though the effect is largest in New England and the East North Central and the East South Central. Lastly, snowfall's negative effect appears to be most pronounced in the South Atlantic and East South Central – two of the three regions with the lowest average snowfall.

Consistent with the earlier findings, the cumulative effects of weather are generally close to zero in all regions, as seen in **Figure 5**. Notable exceptions are that higher temperatures in New England have persistent negative effects on employment growth in both the summer and the winter, and higher temperatures in the Pacific region have persistent positive effects on spring employment growth. Precipitation also has a cumulative negative effect in New England. The number of very cold days have negative cumulative effects in a few regions, especially in New England, the East North Central, and the Mountain region. Lastly, I find that the number of very hot days has negative cumulative effects in several regions and especially in the Pacific region (consistent with the negative contemporaneous effect in that region) and the South Atlantic.

V. Non-Linear and Disaster Effects

In this section, I explore a number of additional dimensions of weather that could potentially affect local employment growth and economic activity. First, I assess the nonlinearity of weather's effects. Second, the effects of extreme weather events are investigated using data on storm damages. Third, I test whether the effects of weather have changed over time. Fourth, I consider whether the effects of weather are different in recessions than in expansions. Lastly, using spatial lag models, I explore whether there are spatial spillovers from weather in one county on employment growth in other counties.

A. Nonlinearities

For the sake of (some) parsimony, the baseline specification allowed for only linear weather effects, though it does allow for the frequency of very cold and very hot days to affect employment separately from the linear effects of temperature. Here I assess the possible nonlinearity of weather effects by adding quadratic terms (for both contemporaneous and lagged variables) to the specification underlying **Table 2**. For this exercise, I drop the number of very hot days and the number of very cold days to ease interpretation of the estimated quadratic temperature effects.

The implied contemporaneous quadratic effect of each weather variable on employment growth is shown in **Figure 6**. Panel A shows the quadratic effect of monthly temperature (average daily high), by season, on monthly employment growth relative to average monthly employment growth in that season: $\hat{\beta}T_s + \hat{\gamma}T_s^2 - \bar{y}_s$, where T_s is temperature in season s and $\bar{y}_s$ is average monthly employment growth in season s. For each season, the implied quadratic temperature effects are shown over the range of temperature values observed in the sample for that season, with the exception of the summer for which values above 110°F are not shown. (The distribution of summer temperature values has a long but very thin far right tail; 110 is the 99.99th percentile.) Panel B shows the implied estimated quadratic effect of (i) average daily precipitation and (ii) average daily snowfall on monthly employment growth relative to average monthly employment growth in the full sample:

$\hat{\beta}X + \hat{\gamma}X^2 - \bar{y}$, where X is either precipitation or snowfall and $\bar{y}$ is average monthly employment growth in the sample. Implied effects are shown for values from the sample minimum, which is 0.0 for both weather variables, to their sample 99.9th percentile, which is 13.34mm for average daily precipitation and 5.27cm for average daily snowfall.

Overall, there is weak evidence of statistically *and* economically significant nonlinear effects. Specifically, spring and fall temperature have statistically significant squared terms (at below the 1% and 5% levels respectively). The squared term for snowfall is significant at below the 1% level while the that for precipitation is significant at below the 10% level. However, as shown in **Figure 6**, in most cases, the nonlinearities are not economically meaningful. Perhaps the one exception is temperature in the fall. At relatively cold temperatures, an added degree of warmth provides a non-trivial boost to employment growth, while at temperature levels around 70° or above an added degree has a roughly zero or even slightly negative effect on employment growth.

B. Natural Disasters

I investigate the effects of natural disasters using county-by-month data from the Federal Emergency Management Authority (FEMA). As mentioned in Section II, I used these data to construct two indicator variables, one indicating whether there was a disaster in the county covering *part* of the month and one indicating whether there was a disaster covering the *entire* month. I augment the county DPD model in equation (1) by including the contemporaneous value and three lags of each of these two indicator variables. I do this for both the models with and without regional heterogeneity.

Table 3 shows the results of estimating the model without regional heterogeneity for private all-industry employment growth. First, notice that the estimated effects on the other variables are virtually unaffected, as can be seen by comparing their coefficients and standard errors to those in **Table 2**. Hence, there is essentially no omitted variable bias in **Table 2** from having excluded disasters. This reflects the very low correlation between weather and disasters in the data, which is partly due to the rarity of disaster and partly due to the fact that the disasters data cover many different types of weather events (e.g., floods and forest fires) as well as non-weather events (e.g., earthquakes). Regarding the direct impact of disasters, I find that they have a large negative contemporaneous impact on employment growth. The impact increases with the duration of the disaster in that the negative impact of disasters covering the entire month is more than double that of disasters lasting only part of the month.

Interestingly, the effect of disasters on employment growth in the subsequent 1-3 months is generally positive. Indeed, this rebound in employment more than offsets the employment decline in the disaster month, such that the cumulative effect on employment after four months is positive and statistically significant. Moreover, the quantitative effect of disasters is large, both contemporaneously and cumulatively. The estimates indicate that, on average, a month-long disaster causes employment to fall by -0.160 percent in that month but to rise by 0.081 percent over four months. A partial-month disaster causes employment to fall by -0.064 percent in the initial month but to rise by 0.073 percent over four months. To put these values in context, the negative contemporaneous effect of a disaster is equivalent to the effect of between three and eight standard deviations – roughly 45 to 120 centimeters (18 to 47 inches) – of snowfall in a month.

Appendix Figures 4 and **5** show the contemporaneous and cumulative effects of disasters, along with the weather variables, by industry. Disasters have a statistically and economically significant negative effect on contemporaneous employment growth in many industries. The effect is largest in those same industries earlier identified as being the most weather-sensitive, namely: Mining and Logging, Construction, and Leisure and Hospitality.

Interestingly, there is a strong positive cumulative effect over four months for the Construction industry, suggesting that property damages caused by disasters induce demand for building reconstruction and repair. This demand might also partly explain the positive cumulative effects (at least for partial-month disasters) found in Retail Trade, which would cover building supplies, and

Professional and Business Services, which would cover contractors and tradespeople. In contrast to these industries, I find a negative cumulative effect of disasters on employment in Education and Health Services. The explanation for this negative cumulative effect is difficult to infer because this sector is rather heterogeneous, but one speculation is that it could reflect a permanent or long-lasting loss of school days, and hence out-of-work school staff, as a result of damage to school buildings.

VI. Spatial Spillovers

In this section, I explore whether there are spatial spillovers from weather in one county to employment growth in other counties. To do so, I extend the county DPD model without regional heterogeneity by adding spatial lag terms. That is, I construct a spatial lag for each weather variable and include its contemporaneous value and three lags in the same model as that underlying **Table 2**. The spatial lag of a variable in a given county and month is a weighted average of the values for that variable in other counties for the same month, where the weights reflect some concept of spatial linkage between each of those other counties and the given county. I construct two different spatial lag measures, one focusing on nearby counties and one focusing on far-away counties. The first uses inverse-distance as weights, where distance is measured between county population centroids and is provided by the Census Bureau. The second uses an equal-weighted average of counties 1,000 or more miles away from the focal county (again based on distance between centroids).

Table 4 shows the results from a model with the inverse-distance spatial lags added to the baseline model. Compared with the results in **Table 2**, the own-county effects are in general qualitatively similar but quantitatively somewhat smaller and less likely to be statistically significant. The spatial lag effects – that is the effects of weather in nearby counties – are often large, though estimated somewhat imprecisely, and generally are in the same direction as the own-county effects. For instance, as in **Table 2**, the own-county effect of temperature in the spring is positive contemporaneously but generally negative in subsequent months. Precipitation in the own county has a negative contemporaneous own-county effect but a positive lagged effect. For both of these weather variables, employment growth in the focal county is affected by weather in other nearby counties in the same direction. An exception to this pattern occurs with temperature's effect on winter employment growth. Winter employment growth in the focal county is boosted by warmer contemporaneous temperatures in that county but negatively affected by warmer temperatures in other nearby counties. I also find that snowfall in nearby counties negatively affects own-county employment growth. This could reflect that snowfall in counties from which workers commute to the focal county could hamper hiring and temporary employment in the focal county.

Next, I estimate this model replacing the inverse-distance spatial lags with the 1000-plus distance spatial lags. The results are shown in **Table 5**. The own-county effects (Panel A) are now very similar to those in **Table 2**. The spatial lag effects are shown in Panel B. Interestingly, they are quite different than the spatial lag effects from nearby counties. In general, unfavorable weather in far-away counties tends to boost employment growth at home. For instance, far-away snowfall boosts near-term employment growth. Similarly, the frequency of very hot days in far-away counties boost employment growth in the focal county. (The same pattern is true for very cold days, but it is not estimated with sufficient precision to be statistically significant.) Also, colder temperatures in the summer in far-away places tends to boost own-county employment growth. One possible explanation for this could be that colder temperatures (holding fixed the number of very hot days) in far-away counties could make the focal county relatively more competitive as a location for summer vacation and recreation. An exception to this general pattern is the positive contemporaneous effect in the winter of temperature in far-away counties.

VII. Adaptation

Do local economies adapt to their specific climates? And does the aggregate economy as a whole adapt, technologically or otherwise, over time to mitigate the economic volatility caused by random weather fluctuations? The first question is essentially a cross-sectional or comparative statics question, asking whether places with colder or wetter or snowier climates, historically, have evolved or adapted their economies to be less sensitive to the deleterious economic effects of cold, rain, and snow? The second question relates to medium-run dynamics, asking whether on average local economies have become more resilient to weather shocks.

Both questions are of critical relevance to the economics of climate change, especially given that consensus climate change projections point to both large geographic shifts in climate across U.S. regions (see, e.g., Sussman, et al. (2014)) and increases in the volatility of weather. For instance, Kahn (2015) cites technological advances such as air conditioning, telecommuting, and supply-chain management software as potentially reducing the disruptiveness of weather shocks on local economic activity and argues that estimates of such adaptation are crucial for estimating the long-run economic effects of climate change. Kahn also argues that geographic mobility is another important margin by which societies can mitigate any economic harm from climate change. The extent to which climate change will induce such internal migration will depend in large part on how well local economies can adapt over the long-run to their specific climates.

I address the first question above by evaluating the extent to which a county's climate mediates the effect of weather deviations on employment growth. I measure a county's climate using the 26-year (1990-2015) mean of each weather variable. I then augment the baseline DPD model by adding interactions of each weather variable (and its lags) with that variable's county-specific mean. To economize of parameters, I include county*calendar-month fixed effects instead of county*calendar-month*decade fixed effects. Note that the inclusion of these fixed effects absorbs the county-specific means, obviating the need to include these uninteracted county means as separate regressors.

The results of this regression are shown in **Table 6**. Panel A shows the coefficients and standard errors on the uninteracted weather variables; Panel B shows those on the interactions with county means. The results are strongly supportive of the hypothesis that local economies do evolve or adapt over the long-run (at least) to their specific climates. In particular, the negative effects of snowfall and precipitation on employment growth and the positive effect of temperature on employment growth in the spring are each attenuated when the respective weather variable is interacted with its county historical average. This is true both for their contemporaneous effects and their cumulative effects over four months (though the cumulative effect of the snowfall interaction is not statistically significant).

The magnitudes of the interactions are substantial. Note that the marginal effect on employment growth (Δl_{ct}) of a one unit (standard deviation) change in a weather variable ($w^k_{c,t-\tau}$), evaluated at its sample mean ($\bar{w}^k_{t-\tau}$), is given by:

$$\frac{\partial \Delta l_{ct}}{\partial w^k_{c,t-\tau}} = \hat{\beta}^k_\tau + \hat{\gamma}^k_\tau \bar{w}^k_{t-\tau} \,,$$

where $\hat{\beta}^k_\tau$ and $\hat{\gamma}^k_\tau$ are the coefficients on the variable and its interaction with the county mean, respectively. Consider first the contemporaneous marginal effect of snowfall. The sample mean of the (standard-deviation-normalized) snowfall variable is approximately 0.4 centimeters (per day). So the snowfall coefficients in **Table 6** of -0.035 and 0.011 imply that the contemporaneous marginal effect of a one standard deviation increase in snowfall (0.51 centimeters) at the sample mean is approximately -0.031 percentage point (p.p.), which is of similar magnitude to the contemporaneous effect of snowfall estimated in **Table 2**. Now consider a county for which average snowfall is two standard deviations, or about 1 centimeter per day (30 centimeters or 12 inches for the month), above the national average. This would reduce, in absolute value, the marginal effect of snowfall from -0.031p.p. to -0.020p.p., or by roughly one-third.

Analogous calculations can be done for precipitation and temperature in the spring. For precipitation, the implied marginal effect at the sample mean is -0.031p.p. (the same as for snowfall), but again this effect is found to be less negative for county's with above average precipitation. In fact, the estimates imply that for a county with normal precipitation two standard deviations above the national average, the marginal effect of an increase in precipitation is *positive* 0.022p.p. This suggests that localities used to receiving a lot of rain have economies structured to take advantage of rainfall, perhaps through water-intensive agricultural production or hydroelectric power generation.

For spring daily-high temperature, the marginal effect at the sample mean, 66° F, is 0.110p.p. However, the marginal effect for a county with normal spring temperature of 82° F, which is two standard deviations above than the sample mean, is just 0.069p.p., which is a little over one-third smaller than the marginal effect at the sample mean. In other words, in counties accustomed to high spring temperatures, short-run temperature increases provide much less boost to spring employment growth than they do in counties accustomed to cold spring months.

The second question discussed above is whether the impacts of weather have changed over time. One simple way to test whether the effects of weather have changed over recent decades is to split the sample in half – 1990m1 to 2002m12 versus 2003m1 to 2015m12 – and test whether the coefficients on weather in the second half of the sample are statistically significantly different from their corresponding coefficients from the first half. To implement this, I start with the baseline no-regional-heterogeneity model for all-industry employment growth and add an interaction between each weather variable (and each of its lags) and a dummy variable equaling one if the observation is in the second half of the sample (and 0 otherwise).

The results of this regression are shown in **Table 7**. As expected, the baseline (non-interacted) weather effects, shown in Panel A, are similar to those in **Table 2**. The second half of the sample interaction effects are shown in Panel B. For most weather variables, there is little if any evidence of time-varying economic effects. However, there are a few interesting exceptions. First, the contemporaneous boosts to employment growth from higher temperatures in both the spring and the fall have grown significantly over time. Furthermore, there is more of a "payback" in the subsequent month – that is, the negative effect on employment growth from higher temperatures one month prior – in the second half of the sample for both spring and fall employment growth. Second, snowfall's detrimental contemporaneous effect on employment growth is much stronger in the first half of the sample, with a coefficient of -0.037, than in the second half, with an implied effect of -0.015 (-0.037 + 0.022) which is not statistically significantly different from zero. The "bounceback" in the subsequent month – that is, the positive effect of one-month lagged snowfall in Panel A – also is much stronger in the first half of the sample. Indeed, the implied one-month lagged snowfall effect in the second half of the sample is near zero (0.029 – 0.034 = -0.005).

In sum, there is evidence that employment growth has become less sensitive over time to snowfall but more sensitive to temperature, at least in the spring and the fall. The increased sensitivity to temperature in the spring and fall could suggest that the economy has not, at least over the past quarter century, adapted technologically or otherwise to become less sensitive to temperature fluctuations. This result is consistent with other recent research. For instance, Deryugina and Hsiang (2014) find no evidence of any change over time in the effect of temperature on annual income at the county level. On the other hand, the decreased sensitivity to snowfall could reflect technological advances facilitating telecommuting and supply-chain/logistics management making local economies more resilient to snowstorms, as suggested in Kahn (2015).

VIII. Potential Mechanisms Underlying Weather's Economic Effects

The results above shed light on the potential mechanisms by which weather fluctuations affect local economic activity. Earlier research has highlighted several potential mechanisms, on both the labor supply and the labor demand sides, by which weather can disrupt or stimulate local economic activity: durable good spending, geographically-immobile production (such as construction and mining & logging), business operations (including commuting of workers, supply-chain functioning, and heating and cooling costs), and discretionary spending.

Some disruptions or stimuli are likely to be transitory. For instance, if poor weather inhibits consumers from buying durables or businesses from buying equipment in that month, they likely will just defer those purchases until a subsequent month. In other words, the intertemporal elasticity of substitution for such spending is high. Likewise, because construction and mining and logging production are tied to specific geographic locations, if poor weather inhibits production in one month, the producers will simply defer the production to future months. These mechanisms likely explain why weather variables such as temperature and rain, which, outside of extreme values, do not strongly affect commuting or business operating costs, are found to have strong contemporaneous effects but no cumulative effects. Indeed, the very term "rain check" is meant to convey the intertemporal substitutability of an activity.

Other weather effects are likely to be persistent, if not permanent. For example, if unfavorable weather discourages people from discretionary spending like going out to eat, they may simply eat at home – i.e., substitute *intra*-temporally to home production. That loss in restaurant sales, and the employment associated with it, are not shifted to future months but rather lost forever (at least until a positive weather shock hits).

In additions, weather events affecting local business operations can lead to persistent effects. For instance, snowstorms can inhibit the ability of people to commute to jobs. For individuals working part-time or on-call, a few days' inability to commute can mean missing a pay period. If that pay period happens to include the 12th of the month, that individual will not be counted as employed in the QCEW data (or the national payroll survey data). The business may be unable to immediately replace those workers with other workers. Snowstorms also disrupt the ability of manufacturers and other businesses to receive parts and raw materials, potentially leading to reduced or suspended production. Extreme heat (days over 90° F) can also disrupt business operations by greatly increasing operating (e.g., cooling) costs. They can also reduce worker productivity (see Graff Zivin and Neidell). Both factors may induce some businesses to temporarily reduce or suspend production.

Consistent with these mechanisms, I found above that the negative employment effects of snowfall and extreme heat are persistent (**Table 2**). I also found that employment in far-away economies is increased by snowfall and extreme heat in a given local economy (**Table 7**). These two results together suggest that weather events that interfere with, or greatly increase the cost of, local producers' getting their employees to work, receiving intermediate inputs (including retail inventories), cooling their facilities, and attracting discretionary consumer spending cause persistent, if not permanent, losses in production. These could be producers of either tradable goods and services, that lose orders to competing far-away producers (even within the same firm) facing more favorable weather, or they could be producers of local non-tradable services like restaurants which suffer when customers substitute toward home production.

IX. Conclusion

Prior economic research on weather has looked at its short-run effect on a host of outcomes, including agricultural yields and land prices, health, mortality, crime, and time-use. Other work has looked at longer-run impacts of climate on macroeconomic growth, house prices, and energy costs. Yet, surprisingly little research has considered the short-run effects of weather on general economic activity. This paper took a first step toward filling that gap. The results herein show that weather has important short-run effects on local economic activity, as measured by all-industry and industry-specific monthly employment growth. Using a county-level dynamic panel data model and monthly data from January 1990 to December 2015, I estimated the effects of temperature (by season), precipitation, snowfall, the frequency of very hot days, the frequency of very cold days, and natural disasters on private nonfarm employment growth. The short-run effects of weather vary considerably across sectors, with the most pronounced effects in Construction, Mining and Logging, Leisure and Hospitality, Retail Trade, and Manufacturing. The effects also vary by region. Natural disasters, both weather and non-weather-related, have large negative effects on employment growth in the month in which they occur, but even larger subsequent positive effects, such that employment is higher four months after a disaster than before the disaster (all else equal). This pattern is especially pronounced in the Construction sector, as one might expect.

Using spatial lag models, I considered the extent to which weather in other counties has spillover effects on employment growth in a given focal county. In general, weather in nearby counties has effects on the focal county's employment growth of the same sign but smaller magnitude as the effects of own-county weather, consistent with positive localized spillovers. Weather in far-away counties, on the other hand, tends to have opposite effects from those of own-county weather, suggesting that local economies compete to some extent with distant economies, with unfavorable weather putting local economies at least temporarily at a disadvantage.

Finally, I investigated the extent to which local economies have evolved, or are able to adapt, to mitigate their sensitivity to random weather fluctuations. I first considered whether the economy in places with a certain type of climate – whether it be high seasonal temperatures or high amounts of precipitation or snowfall – has evolved or adapted to be less sensitive to short-run fluctuations in that type of weather. I find strong evidence supporting this hypothesis, in that the sizable marginal effects of spring temperature increases, precipitation, and snowfall for the average county are much smaller for counties with high historical averages for these variables. Next, I asked whether the effects of weather have changed over time. Local economies appear to have become more sensitive to temperature increases, at least in the spring and fall, but less sensitive to snowfall. Thus, the evidence on whether local economies have, on average, adapted technologically or otherwise to be more resilient to weather fluctuations is mixed, with no evidence of increased resiliency to temperature swings but strong evidence that snow-related disruptions have become increasingly minor.

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Table 1. Summary Statistics

Panel A. Full Sample (All Months)

	Mean	Standard Deviation	Minimum	Maximum
Employment (All-Industry)	32,603	121,695	0	3,799,204
Employment growth rate (%)	0.079	2.791	-10.732	10.329
Avg. daily high temp	66.64	18.12	1.18	121.13
Avg. daily precipitation (mm)	2.73	1.94	0	76.20
Avg. daily snowfall (cm)	0.18	0.51	0	27.90
% days high temp >90F	0.10	0.21	0	1
% days low temp <30F	0.24	0.34	0	1
Dummy: FEMA disaster for part of month	0.04	0.19	0	1
Dummy: FEMA disaster for full month	0.01	0.11	0	1

Panel B. Winter Months (Dec., Jan., Feb.)

	Mean	Standard Deviation	Minimum	Maximum
Employment (All-Industry)	32,224	120,963	0	3,799,204
Employment growth rate (%)	-0.921	2.860	-10.732	10.329
Avg. daily high temp	45.69	12.53	1.18	84.26
Avg. daily precipitation (mm)	2.31	1.92	0	76.20
Avg. daily snowfall (cm)	0.50	0.77	0	23.50
% days high temp >90F	0.00	0.00	0	0
% days low temp <30F	0.64	0.31	0	1
Dummy: FEMA disaster for part of month	0.04	0.19	0	1
Dummy: FEMA disaster for full month	0.01	0.08	0	1

Panel C. Spring Months (Mar., Apr., May)

	Mean	Standard Deviation	Minimum	Maximum
Employment (All-Industry)	32,365	121,003	0	3,762,892
Employment growth rate (%)	1.317	2.500	-10.732	10.329
Avg. daily high temp	66.44	11.95	21.33	106.80
Avg. daily precipitation (mm)	2.88	1.87	0	49.30
Avg. daily snowfall (cm)	0.15	0.43	0	19.10
% days high temp >90F	0.02	0.08	0	1
% days low temp <30F	0.18	0.26	0	1
Dummy: FEMA disaster for part of month	0.04	0.20	0	1
Dummy: FEMA disaster for full month	0.02	0.14	0	1

Panel D. Summer Months (Jun., Jul., Aug.)

	Mean	Standard Deviation	Minimum	Maximum
Employment (All-Industry)	32,933	122,150	0	3,776,688
Employment growth rate (%)	0.580	2.558	-10.732	10.329
Avg. daily high temp	85.92	5.95	59.68	121.13
Avg. daily precipitation (mm)	3.13	1.97	0	67.30
Avg. daily snowfall (cm)	0.00	0.02	0	6.77
% days high temp >90F	0.31	0.30	0	1
% days low temp <30F	0.00	0.00	0	0
Dummy: FEMA disaster for part of month	0.04	0.19	0	1
Dummy: FEMA disaster for full month	0.02	0.13	0	1

Panel E. Fall Months (Sep., Oct., Nov.)

	Mean	Standard Deviation	Minimum	Maximum
Employment (All-Industry)	32,892	122,654	0	3,769,978
Employment growth rate (%)	-0.669	2.624	-10.732	10.329
Avg. daily high temp	68.49	12.80	20.36	111.12
Avg. daily precipitation (mm)	2.58	1.91	0	55.10
Avg. daily snowfall (cm)	0.08	0.35	0	27.90
% days high temp >90F	0.05	0.13	0	1
% days low temp <30F	0.15	0.23	0	1
Dummy: FEMA disaster for part of month	0.03	0.17	0	1
Dummy: FEMA disaster for full month	0.00	0.06	0	1

Table 2. Contemporaneous and Lagged Weather Effects on Employment Growth
Industry: All Private Industries

	(1) Contemporaneous	(2) 1st lag	(3) 2nd lag	(4) 3rd lag	(5) Cumulative effect
Avg. daily high temp - Spring	0.121***	-0.043***	-0.050***	-0.037***	-0.009
	(0.009)	(0.009)	(0.009)	(0.009)	(0.014)
Avg. daily high temp - Summer	0.054***	-0.032***	-0.032***	-0.010	-0.020
	(0.013)	(0.012)	(0.011)	(0.009)	(0.017)
Avg. daily high temp - Fall	0.029***	0.000	-0.033**	0.015	0.010
	(0.010)	(0.012)	(0.013)	(0.014)	(0.019)
Avg. daily high temp - Winter	0.071***	-0.014	-0.043***	-0.030**	-0.016
	(0.010)	(0.010)	(0.011)	(0.012)	(0.018)
Precipitation (mm)	-0.023***	0.016***	0.009**	0.000	0.002
	(0.004)	(0.004)	(0.003)	(0.004)	(0.007)
Snowfall (cm)	-0.020***	0.002	0.006	-0.002	-0.015**
	(0.004)	(0.004)	(0.004)	(0.004)	(0.006)
% days high temp >90F	-0.018**	-0.007	-0.007	-0.020**	-0.052***
	(0.008)	(0.009)	(0.008)	(0.008)	(0.013)
% days low temp <30F	-0.016	-0.020	0.008	-0.000	-0.028
	(0.014)	(0.013)	(0.014)	(0.012)	(0.021)
N	960372				
Counties	3108				
Months	309				
R2	0.572				

***p<0.01, **p<0.05, *p<0.10

Table 3. Contemporaneous and Lagged Weather Effects on Employment Growth
Industry: All Private Industries

	(1) Contemporaneous	(2) 1st lag	(3) 2nd lag	(4) 3rd lag	(5) Cumulative effect
Avg. daily high temp - Spring	0.121***	-0.045***	-0.050***	-0.036***	-0.010
	(0.009)	(0.009)	(0.009)	(0.009)	(0.014)
Avg. daily high temp - Summer	0.053***	-0.031***	-0.032***	-0.009	-0.019
	(0.013)	(0.012)	(0.011)	(0.009)	(0.017)
Avg. daily high temp - Fall	0.031***	0.001	-0.033**	0.015	0.014
	(0.010)	(0.012)	(0.013)	(0.014)	(0.019)
Avg. daily high temp - Winter	0.071***	-0.014	-0.044***	-0.030**	-0.017
	(0.010)	(0.010)	(0.011)	(0.012)	(0.018)
Precipitation (mm)	-0.020***	0.014***	0.006*	-0.002	-0.002
	(0.004)	(0.004)	(0.004)	(0.004)	(0.007)
Snowfall (cm)	-0.020***	0.002	0.006	-0.003	-0.015**
	(0.004)	(0.004)	(0.004)	(0.003)	(0.006)
% days high temp >90F	-0.018**	-0.008	-0.009	-0.019**	-0.054***
	(0.008)	(0.009)	(0.008)	(0.008)	(0.013)
% days low temp <30F	-0.015	-0.020	0.006	-0.002	-0.032
	(0.014)	(0.013)	(0.014)	(0.012)	(0.021)
Dummy: FEMA disaster for part of month	-0.064***	0.085***	0.014	0.038***	0.073***
	(0.015)	(0.015)	(0.015)	(0.013)	(0.020)
Dummy: FEMA disaster for full month	-0.160***	0.212***	-0.004	0.033	0.081**
	(0.033)	(0.040)	(0.035)	(0.031)	(0.035)
N	960372				
Counties	3108				
Months	309				
R2	0.572				

***p<0.01, **p<0.05, *p<0.10

Table 4: Model Including Spatial Lags (Inverse-Distance)

Panel A: Own-County Effects

	(1) Contemporaneous	(2) 1st lag	(3) 2nd lag	(4) 3rd lag	(5) Cumulative effect
Avg. daily high temp - Spring	0.055***	-0.024	0.019	-0.027**	0.022
	(0.017)	(0.017)	(0.016)	(0.014)	(0.022)
Avg. daily high temp - Summer	-0.007	-0.025	-0.035*	0.005	-0.062**
	(0.021)	(0.020)	(0.020)	(0.016)	(0.026)
Avg. daily high temp - Fall	0.019	-0.006	-0.018	-0.011	-0.016
	(0.018)	(0.021)	(0.021)	(0.021)	(0.029)
Avg. daily high temp - Winter	0.069***	0.002	-0.082***	0.013	0.002
	(0.018)	(0.020)	(0.021)	(0.021)	(0.030)
Precipitation (mm)	-0.007*	0.009*	0.010**	0.004	0.016*
	(0.004)	(0.005)	(0.004)	(0.005)	(0.008)
Snowfall (cm)	0.004	-0.008*	0.003	-0.004	-0.005
	(0.004)	(0.004)	(0.004)	(0.004)	(0.006)
% days high temp >90F	-0.007	0.003	0.007	-0.003	0.000
	(0.010)	(0.011)	(0.010)	(0.011)	(0.016)
% days low temp <30F	-0.001	-0.008	-0.017	0.005	-0.021
	(0.018)	(0.018)	(0.017)	(0.016)	(0.029)

Panel B: Spatial Lag Effects

	(1) Contemporaneous	(2) 1st lag	(3) 2nd lag	(4) 3rd lag	(5) Cumulative effect
Avg. daily high temp - Spring	0.148***	-0.044	-0.199***	-0.040	-0.135*
	(0.053)	(0.054)	(0.051)	(0.046)	(0.078)
Avg. daily high temp - Summer	0.221***	-0.019	0.025	-0.062	0.164*
	(0.077)	(0.064)	(0.062)	(0.050)	(0.087)
Avg. daily high temp - Fall	0.000	0.034	-0.033	0.144*	0.145
	(0.055)	(0.065)	(0.074)	(0.076)	(0.102)
Avg. daily high temp - Winter	-0.088*	-0.030	0.137**	-0.140**	-0.121
	(0.053)	(0.060)	(0.064)	(0.065)	(0.101)
Precipitation (mm)	-0.039***	0.016	-0.003	-0.015	-0.040**
	(0.010)	(0.011)	(0.010)	(0.010)	(0.019)
Snowfall (cm)	-0.142***	0.057***	0.010	0.012	-0.063*
	(0.019)	(0.019)	(0.017)	(0.016)	(0.032)
% days high temp >90F	-0.042	-0.038	-0.055	-0.081**	-0.217***
	(0.037)	(0.037)	(0.037)	(0.038)	(0.057)
% days low temp <30F	-0.062	-0.048	0.116	-0.087	-0.081
	(0.074)	(0.078)	(0.076)	(0.071)	(0.132)
N	960372				
Counties	3108				
Months	309				
R2	0.572				

***p<0.01, **p<0.05, *p<0.10

Table 5: Model Including Spatial Lags (Donut 1000+ mi.)

Panel A: Own-County Effects

	(1) Contemporaneous	(2) 1st lag	(3) 2nd lag	(4) 3rd lag	(5) Cumulative effect
Avg. daily high temp - Spring	0.104***	-0.035***	-0.025**	-0.031***	0.013
	(0.012)	(0.012)	(0.012)	(0.010)	(0.016)
Avg. daily high temp - Summer	0.031**	-0.028**	-0.042***	-0.010	-0.049**
	(0.016)	(0.014)	(0.013)	(0.011)	(0.020)
Avg. daily high temp - Fall	0.035***	-0.013	-0.031**	0.006	-0.002
	(0.013)	(0.015)	(0.015)	(0.015)	(0.023)
Avg. daily high temp - Winter	0.085***	-0.021	-0.065***	-0.033**	-0.035
	(0.013)	(0.013)	(0.015)	(0.015)	(0.022)
Precipitation (mm)	-0.021***	0.016***	0.009**	-0.000	0.004
	(0.004)	(0.004)	(0.004)	(0.004)	(0.007)
Snowfall (cm)	-0.018***	0.002	0.007*	-0.003	-0.013**
	(0.004)	(0.004)	(0.004)	(0.003)	(0.006)
% days high temp >90F	-0.011	-0.001	-0.007	-0.011	-0.030**
	(0.009)	(0.009)	(0.009)	(0.009)	(0.014)
% days low temp <30F	-0.015	-0.016	0.009	0.003	-0.018
	(0.015)	(0.014)	(0.014)	(0.013)	(0.022)

Panel B: Spatial Lag Effects

	(1) Contemporaneous	(2) 1st lag	(3) 2nd lag	(4) 3rd lag	(5) Cumulative effect
Avg. daily high temp - Spring	-0.018	0.033	0.070***	0.015	0.099**
	(0.024)	(0.027)	(0.024)	(0.023)	(0.040)
Avg. daily high temp - Summer	-0.106***	0.003	-0.030	-0.005	-0.138***
	(0.041)	(0.030)	(0.027)	(0.022)	(0.046)
Avg. daily high temp - Fall	0.028	-0.049	0.015	-0.082**	-0.089
	(0.024)	(0.030)	(0.037)	(0.040)	(0.057)
Avg. daily high temp - Winter	0.063**	-0.017	-0.057*	-0.016	-0.027
	(0.026)	(0.028)	(0.030)	(0.028)	(0.048)
Precipitation (mm)	0.008	0.004	-0.001	0.002	0.012
	(0.007)	(0.007)	(0.007)	(0.007)	(0.013)
Snowfall (cm)	0.044***	-0.017	0.023*	-0.027**	0.023
	(0.013)	(0.014)	(0.013)	(0.012)	(0.022)
% days high temp >90F	0.047*	0.035*	-0.010	0.063**	0.134***
	(0.024)	(0.021)	(0.024)	(0.025)	(0.040)
% days low temp <30F	0.024	0.040	-0.024	0.048	0.088
	(0.046)	(0.048)	(0.046)	(0.044)	(0.079)
N	960372				
Counties	3108				
Months	309				
R2	0.572				

***p<0.01, **p<0.05, *p<0.10

Table 6: Weather's Effects on Employment Growth, Interacting Weather with Local Climate (26-year Means)

Panel A: Non-Interacted Effects

	(1) Contemporaneous	(2) 1st lag	(3) 2nd lag	(4) 3rd lag	(5) Cumulative effect
Avg. daily high temp - Spring	0.271***	-0.054*	-0.001	-0.060**	0.156***
	(0.043)	(0.033)	(0.031)	(0.028)	(0.050)
Avg. daily high temp - Summer	0.008	0.036	-0.066	-0.048	-0.070
	(0.160)	(0.107)	(0.076)	(0.046)	(0.165)
Avg. daily high temp - Fall	0.043	-0.185**	0.223	-0.270	-0.190
	(0.040)	(0.082)	(0.145)	(0.167)	(0.211)
Avg. daily high temp - Winter	0.061**	-0.009	-0.107***	-0.041	-0.096*
	(0.030)	(0.032)	(0.036)	(0.043)	(0.052)
Precipitation (mm)	-0.051***	0.007	0.013	-0.004	-0.035*
	(0.011)	(0.012)	(0.012)	(0.011)	(0.020)
Snowfall (cm)	-0.035***	0.010*	0.015**	-0.006	-0.016
	(0.006)	(0.006)	(0.006)	(0.006)	(0.010)
% days high temp >90F	0.001	-0.006	0.007	-0.030**	-0.027
	(0.013)	(0.014)	(0.014)	(0.014)	(0.023)
% days low temp <30F	-0.010	0.020	-0.051*	-0.012	-0.053
	(0.026)	(0.026)	(0.027)	(0.026)	(0.047)

Panel B: Interacted Effects

	(1) Contemporaneous	(2) 1st lag	(3) 2nd lag	(4) 3rd lag	(5) Cumulative effect
Avg. daily high temp - Spring	-0.011***	0.000	-0.004	0.002	-0.012***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)
Avg. daily high temp - Summer	0.001	-0.003	0.002	0.003	0.003
	(0.009)	(0.006)	(0.005)	(0.003)	(0.009)
Avg. daily high temp - Fall	-0.001	0.011**	-0.014*	0.015*	0.011
	(0.003)	(0.005)	(0.008)	(0.009)	(0.012)
Avg. daily high temp - Winter	0.001	0.000	0.005*	0.001	0.008*
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)
Precipitation (mm)	0.014***	0.005	-0.000	0.003	0.022**
	(0.005)	(0.006)	(0.006)	(0.005)	(0.010)
Snowfall (cm)	0.011***	-0.005	-0.004*	0.002	0.003
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)
% days high temp >90F	-0.006	-0.003	-0.002	0.004	-0.006
	(0.006)	(0.006)	(0.006)	(0.007)	(0.010)
% days low temp <30F	0.006	-0.017	0.038**	0.011	0.038
	(0.016)	(0.017)	(0.016)	(0.015)	(0.029)
N	960372				
Counties	3108				
Months	309				
R2	0.505				

***p<0.01, **p<0.05, *p<0.10

Table 7: Weather's Effects on Employment Growth, Interacting Weather with Second-Half-of-Sample Dummy

Panel A: Non-Interacted Effects

	(1) Contemporaneous	(2) 1st lag	(3) 2nd lag	(4) 3rd lag	(5) Cumulative effect
Avg. daily high temp - Spring	0.102***	-0.026**	-0.060***	-0.024*	-0.008
	(0.012)	(0.013)	(0.013)	(0.012)	(0.015)
Avg. daily high temp - Summer	0.069***	-0.022	-0.043***	-0.006	-0.003
	(0.019)	(0.017)	(0.016)	(0.012)	(0.019)
Avg. daily high temp - Fall	0.011	0.029	-0.068***	0.030	0.001
	(0.014)	(0.019)	(0.020)	(0.020)	(0.022)
Avg. daily high temp - Winter	0.052***	0.005	-0.042**	-0.039**	-0.025
	(0.014)	(0.017)	(0.018)	(0.016)	(0.019)
Precipitation (mm)	-0.022***	0.017***	0.002	0.011**	0.009
	(0.006)	(0.005)	(0.005)	(0.006)	(0.009)
Snowfall (cm)	-0.038***	0.029***	0.003	0.008	0.002
	(0.010)	(0.009)	(0.008)	(0.008)	(0.013)
% days high temp >90F	-0.026**	-0.002	0.001	-0.031***	-0.058***
	(0.012)	(0.013)	(0.013)	(0.012)	(0.017)
% days low temp <30F	-0.016	-0.013	-0.005	-0.005	-0.039
	(0.018)	(0.019)	(0.019)	(0.017)	(0.027)

Panel B: Interacted Effects

	(1) Contemporaneous	(2) 1st lag	(3) 2nd lag	(4) 3rd lag	(5) Cumulative effect
Avg. daily high temp - Spring	0.036**	-0.032*	0.019	-0.020	0.003
	(0.017)	(0.018)	(0.017)	(0.016)	(0.012)
Avg. daily high temp - Summer	-0.034	-0.018	0.022	0.000	-0.030
	(0.024)	(0.022)	(0.020)	(0.015)	(0.018)
Avg. daily high temp - Fall	0.028*	-0.050**	0.068***	-0.027	0.018
	(0.016)	(0.022)	(0.025)	(0.023)	(0.019)
Avg. daily high temp - Winter	0.028	-0.028	-0.004	0.020	0.016
	(0.017)	(0.020)	(0.022)	(0.021)	(0.015)
Precipitation (mm)	0.000	-0.003	0.013*	-0.020***	-0.010
	(0.007)	(0.007)	(0.007)	(0.007)	(0.011)
Snowfall (cm)	0.022**	-0.034***	0.004	-0.012	-0.019
	(0.010)	(0.010)	(0.009)	(0.008)	(0.014)
% days high temp >90F	0.018	-0.013	-0.015	0.022	0.011
	(0.015)	(0.015)	(0.015)	(0.014)	(0.019)
% days low temp <30F	0.001	-0.017	0.025	0.010	0.020
	(0.022)	(0.024)	(0.024)	(0.022)	(0.030)
N	960372				
Counties	3108				
Months	309				
R2	0.572				

***p<0.01, **p<0.05, *p<0.10

Figure 1. Short-Run Dynamic Effects of Weather on Private Nonfarm Employment Growth

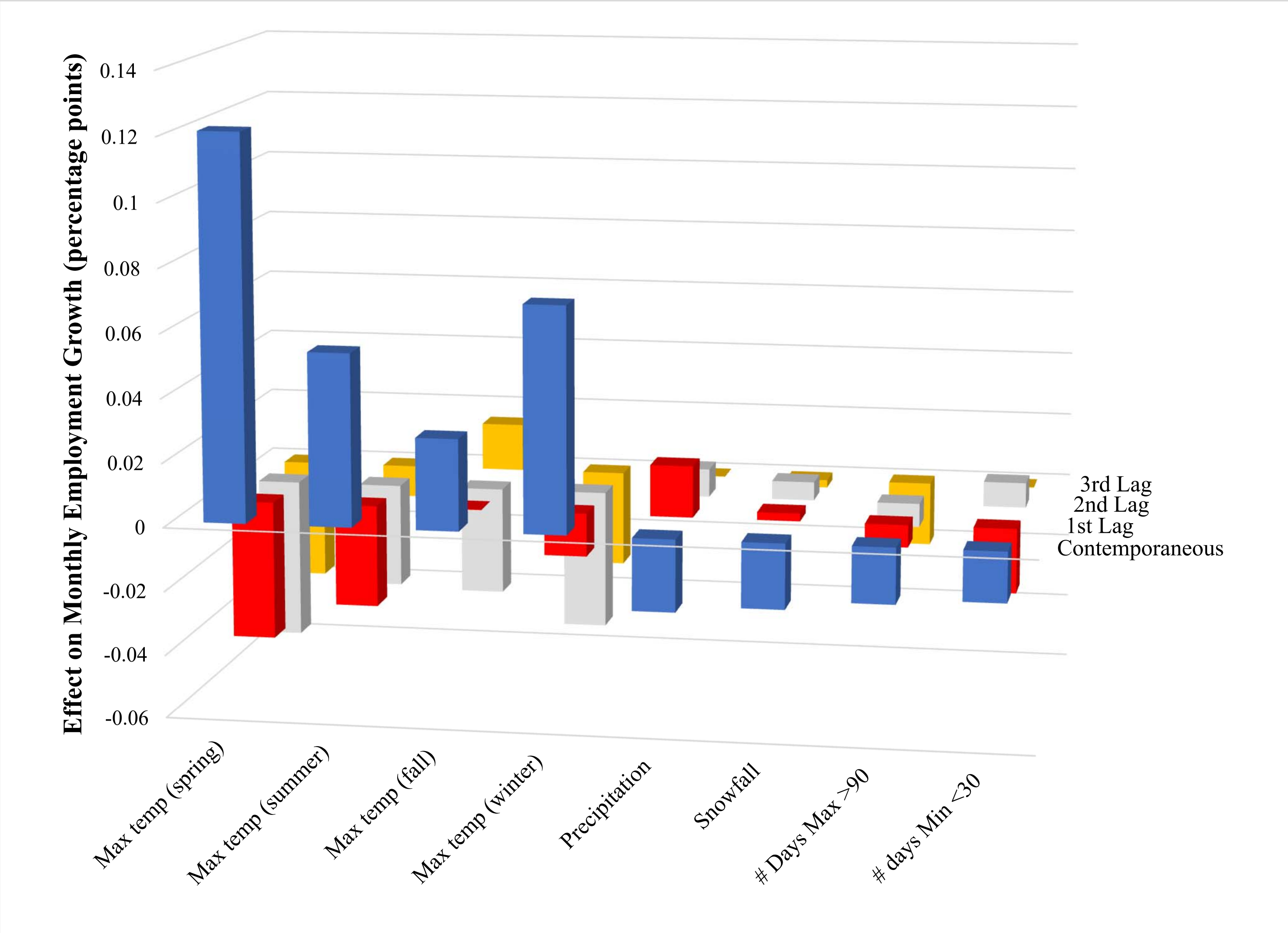
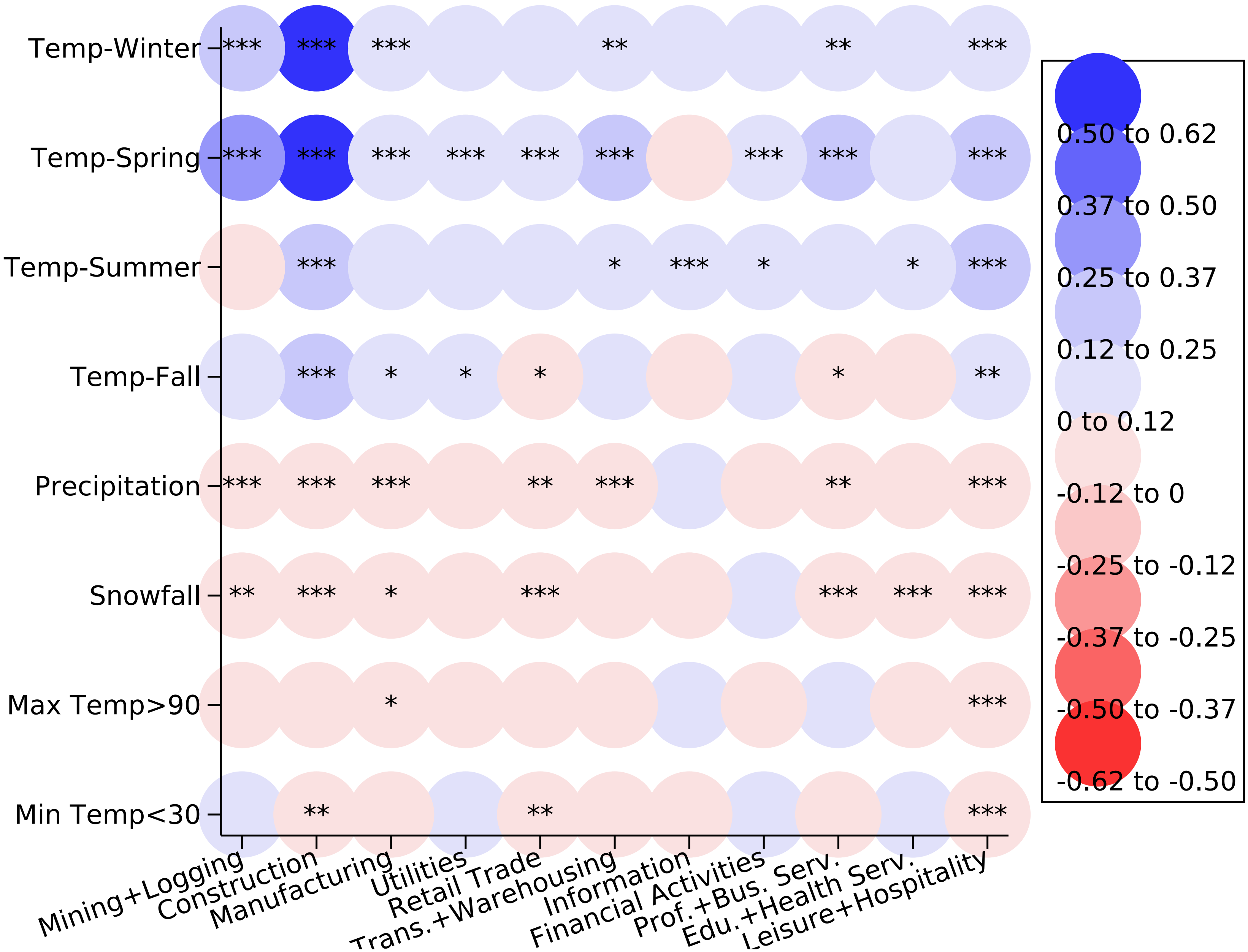
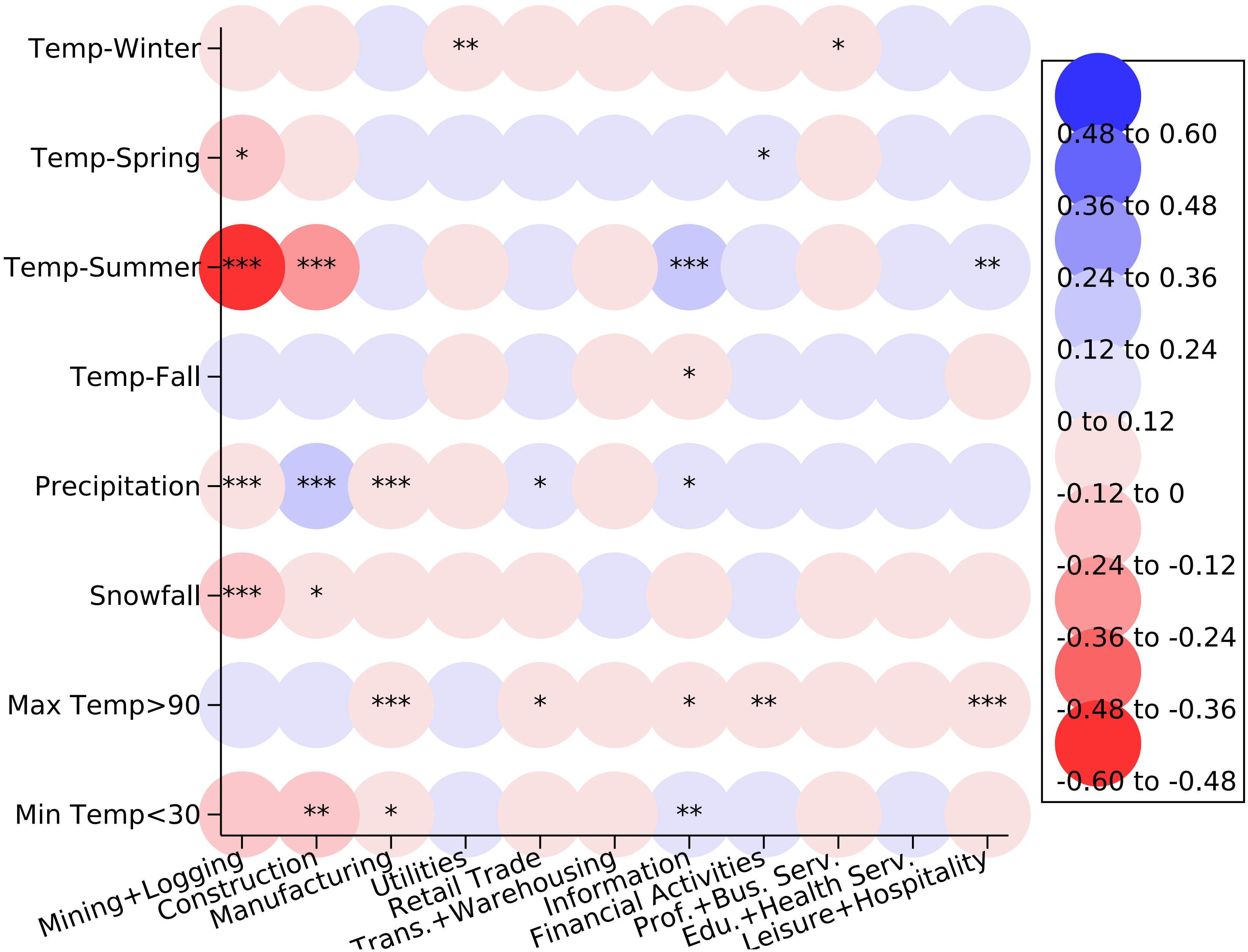


Figure 2. Heatmap of Contemporaneous Weather Effects By Industry



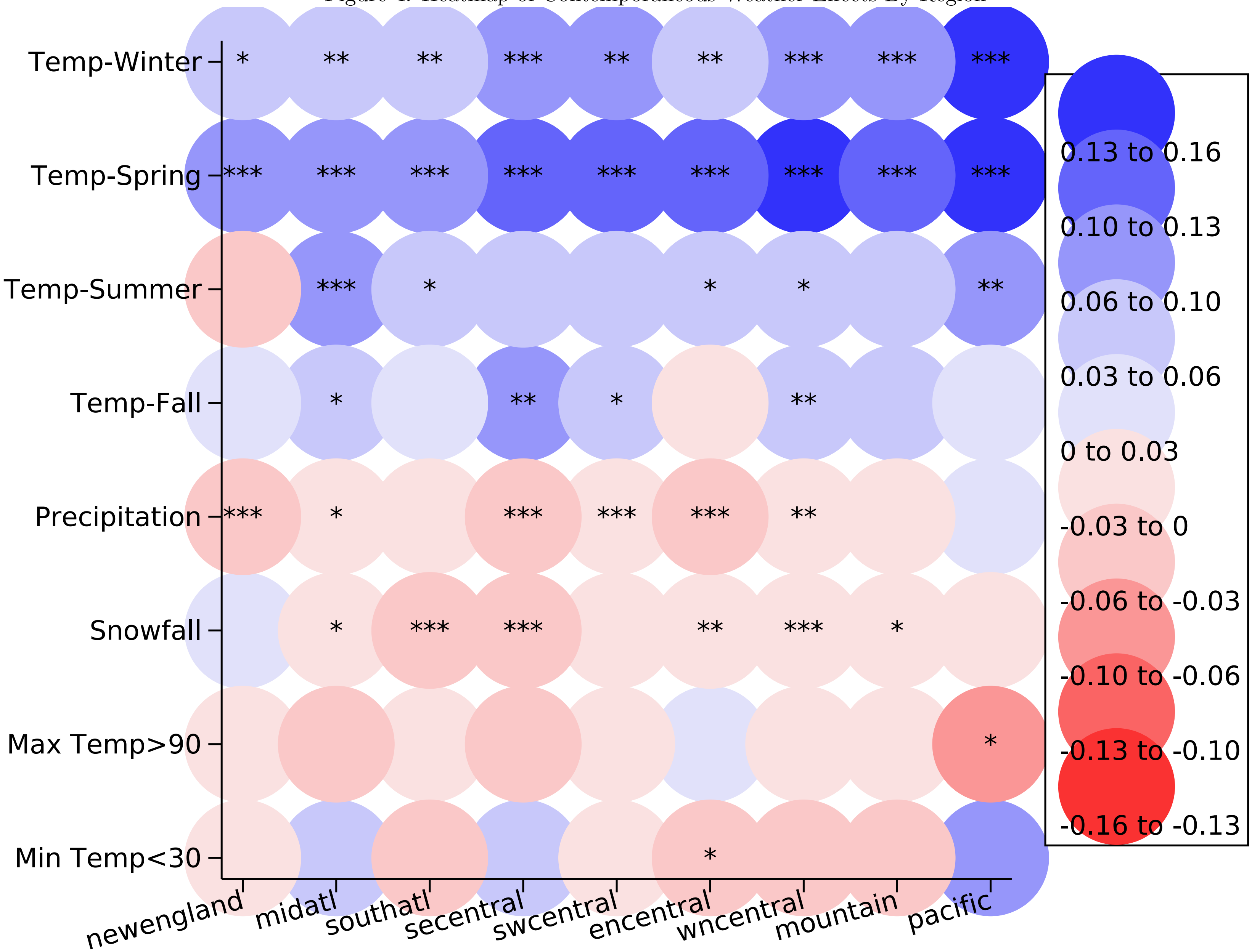
Notes: Each cell of heatmap above represents the coefficient on the weather variable indicated on the y-axis on employment growth in the industry indicated on the x-axis. Positive values are shown as blue circles, while negative values are shown as red, with darker shading for larger (in absolute values) coefficients. The stars indicate statistical significance: ***p<.01, ** p<.05, * p<.10

Figure 3. Heatmap of Cumulative Weather Effects By Industry



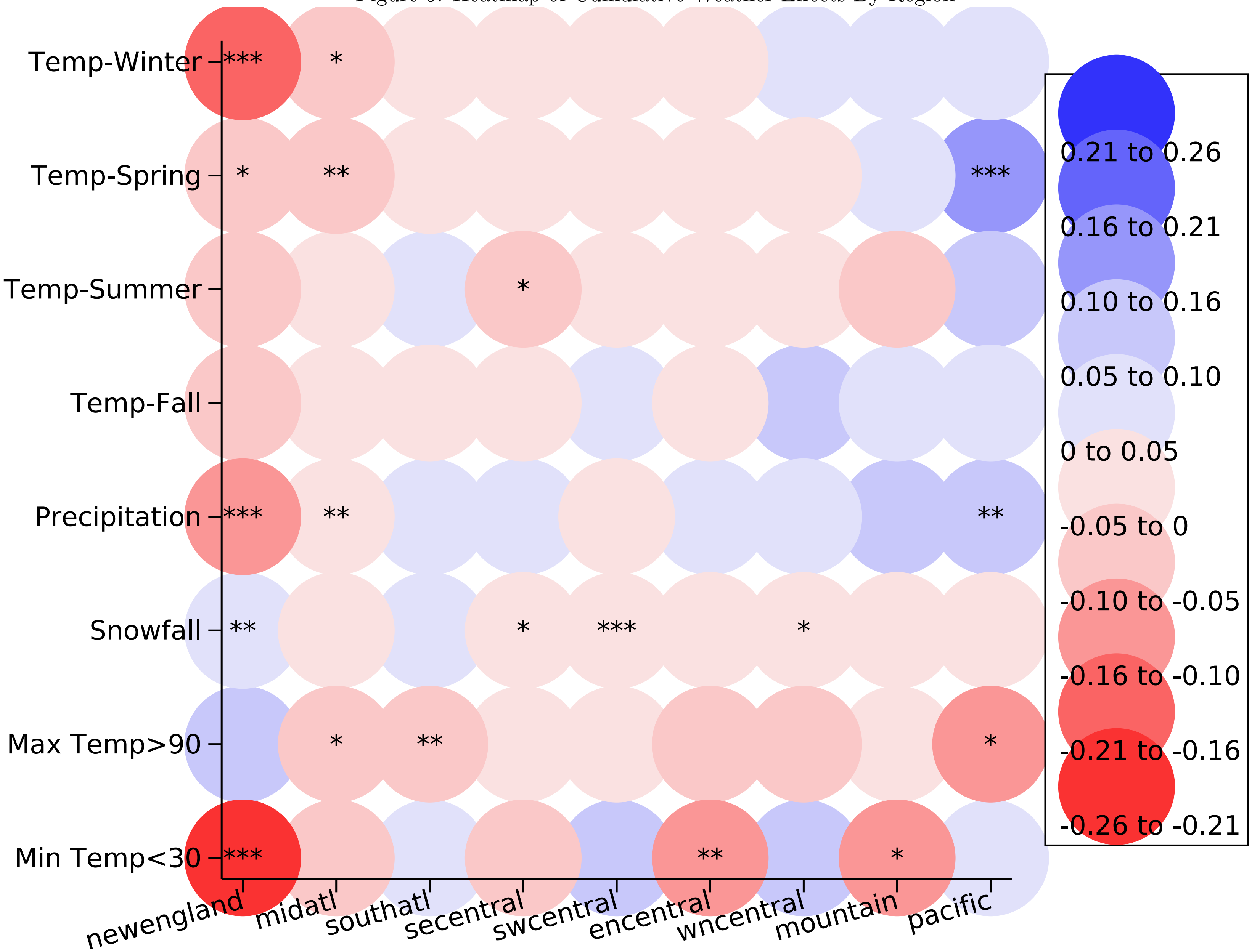
Notes: Each cell of heatmap above represents the coefficient on the weather variable indicated on the y-axis on employment growth in the industry indicated on the x-axis. Positive values are shown as blue circles, while negative values are shown as red, with darker shading for larger (in absolute values) coefficients. The stars indicate statistical significance: ***p<.01, ** p<.05, * p<.10

Figure 4. Heatmap of Contemporaneous Weather Effects By Region



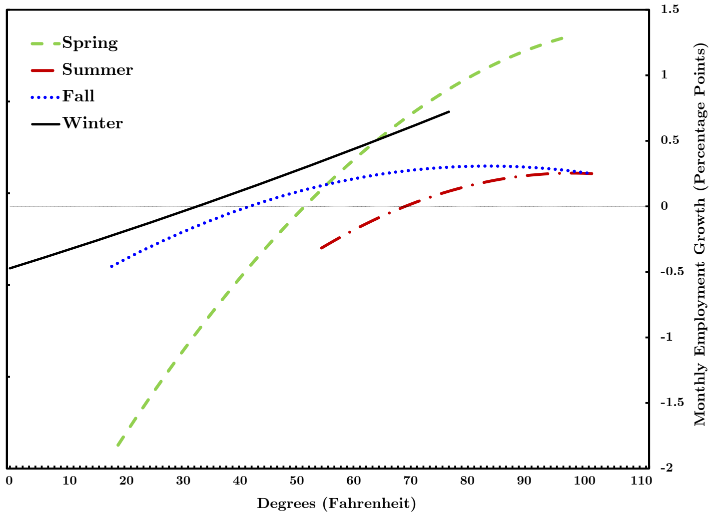
Notes: Each cell of heatmap above represents the coefficient on the weather variable indicated on the y-axis on employment growth in the industry indicated on the x-axis. Positive values are shown as blue circles, while negative values are shown as red, with darker shading for larger (in absolute values) coefficients. The stars indicate statistical significance: ***p<.01, ** p<.05, * p<.10

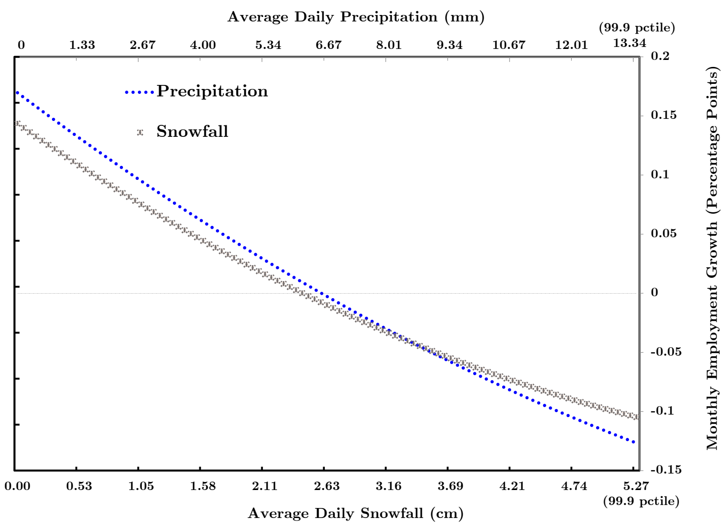
Figure 5. Heatmap of Cumulative Weather Effects By Region



Notes: Each cell of heatmap above represents the coefficient on the weather variable indicated on the y-axis on employment growth in the industry indicated on the x-axis. Positive values are shown as blue circles, while negative values are shown as red, with darker shading for larger (in absolute values) coefficients. The stars indicate statistical significance: ***p<.01, ** p<.05, * p<.10

Figure 6. Estimated Quadratic Relationship Between Contemporaneous Weather and Employment Growth





Notes: Top panel shows the estimated implied quadratic effect of temperature (average daily high per month), by season, on monthly employment growth relative to average monthly employment growth in that season: $\hat{\beta}T_s + \hat{\gamma}T_s^2 - \bar{y}_s$, where T_s is temperature in season s and $\bar{y}_s$ is average monthly employment growth in season s. For each season, the implied quadratic temperature effects are shown over the range of temperature values observed in the sample for that season, though monthly temperature values above 110 degrees are not shown because they are very rare and cause the range of the graph to expand greatly. The bottom panel shows the implied estimated quadratic effect of (i) average daily precipitation and (ii) average daily snowfall on monthly employment growth relative to average monthly employment growth in the full sample: $\hat{\beta}X + \hat{\gamma}X^2 - \bar{y}$, where X is either precipitation or snowfall and $\bar{y}$ is average monthly employment growth in the sample. Implied effects are shown for values from the sample minimum, which is 0.0 for both weather variables, to their sample 99.9th percentile, which is 13.34mm for average daily precipitation and 5.27cm for average daily snowfall.

Online Appendix A

A Closer Look at Weather's Effect on Construction Activity

A priori, one might expect the Construction sector to be particularly weather-sensitive, and the results in the **Section IV** strongly confirmed that prior. Construction employment growth was found to be positively affected in the near-term by temperature, especially in the spring and winter, and negatively affected by the frequency of very cold days, by snowfall, and by precipitation. Indeed, by comparing the results for Construction in **Appendix Table 2** with those for all-industry in **Table 2**, one can see that the magnitude of each weather variable's contemporaneous effect is several times larger for Construction. A few weather variables also were found to have significant cumulative effects on Construction employment. Thus, in this Appendix, I take a closer look at the particular impacts of weather on Construction activity. First, I explore weather's effects on Construction employment growth by region. Second, I estimate the effects of weather on new building permits and compare the results to those for Construction employment growth.

The heatmaps in **Appendix Figures 6** and **7** graph the contemporaneous and cumulative effects, respectively, of weather on Construction employment growth by region. Starting with the contemporaneous effects, we see a number of clear patterns. First, the strong contemporaneous boost from temperature in the spring and winter is apparent in all regions. However, the contemporaneous impacts of temperature in the summer and fall – which tend to be modest – vary by region. In these seasons, warmer temperatures – relative to local seasonal norms which are captured by the county*calendar-month*decade fixed effects – are detrimental to immediate construction employment growth in New England. In other regions, warmer temperatures in these two seasons have either no effect or a positive effect. Second, the negative effects of precipitation and snowfall on construction employment are broad-based across regions. Third, the impact of very hot days varies considerably across regions. For instance, it is negative and significant in the West North Central and the Pacific region – regions less accustomed to days above 90°F – while it is positive and significant in the West South Central, where such days are not uncommon. Lastly, the contemporaneous positive effect of storm damages on construction employment growth is found to be broad-based, though it is only statistically significant in the New England, Mountain, and Pacific regions.

Appendix Figure 7 shows that, despite the positive effect in general of warmer temperatures on contemporaneous employment growth, warmer temperatures in many cases have negative cumulative effects. The converse is true for precipitation, which has negative contemporaneous effects in general, but positive cumulative effects except in New England. The number of very hot days has no significant cumulative effect, but the number of very cold days has a negative cumulative effect in New England and in the Mountain region. It is possible that these regions, which tend to have long, cold winters, generally have relatively narrow seasonal windows for doing construction work. So if very cold days stretch over two to four months, construction firms may miss this window for starting and completing projects, leading to persistently, if not permanently, lower employment. Lastly, we see that, in a number of regions, particularly the New England, South-Atlantic, Southwest Central, and Pacific regions, natural disasters negatively affect contemporaneous Construction employment growth, both positively affect it cumulatively over four months.

Next, I estimate the local effects of weather on new building permits. Specifically, using Census Bureau data on building permits by county and month for the same sample period as used for employment growth, namely January 1990 through December 2015, I estimate the same county DPD model with regional heterogeneity, as in equation (1), but replacing the monthly log change in employment with the monthly log change in permits. The results provide something of a cross-check on the validity of the construction employment results, as well as providing more of a focus on *new* construction.

The data measure permit issuances by local jurisdictions for new privately-owned residential buildings (both single- and multi-unit) and are derived from the Census Bureau's Residential Permit Use Survey (SUP). Unfortunately, data on residential construction *starts* are not available at the county level. However, according to the Census Bureau, the average time between permits and starts for single-unit buildings, which are nearly 90% of residential buildings in the permits data, is a little under one month.[21] (The average interval for multi-unit buildings is about two months.)

The results are shown graphically in **Appendix Figures 8** and **9**. As expected, the results are generally similar to those for construction employment growth in **Appendix Figures 6** and **7**. However, there are a couple of interesting differences. First, unlike for employment, the contemporaneous impact of temperature on permits is much stronger in the winter than in the spring. This could be related to the distinction between new and ongoing construction activity. Warmer winter temperatures may facilitate both new and ongoing construction projects, while warmer temperatures in the spring could facilitate ongoing projects (which do not require new permits) more so than the initiation of new projects. Note that for both permits and construction employment, warmer temperatures tend to have negative cumulative effects on activity in the spring. This may reflect that warmer temperatures during the winter pull forward construction activity from the spring.

Second, while I found earlier that disasters have negative contemporaneous effects but positive cumulative effects on construction employment, they have negative effects on new building permits in the near-term and essentially no effect over four months. This is somewhat revealing. It may well reflect that reconstruction and repair work following major storms do require construction employment but do not require permits for *new* construction. An exception would be rare catastrophic storms requiring new buildings to replace demolished old buildings, but even in these cases it would likely take many months before permits for the new buildings are applied for. Indeed, such delayed demand for new permits after major storms could explain the positive cumulative effect of disasters on permits in a couple regions found in **Appendix Figure 9**.

[21] See https://www.census.gov/construction/nrc/pdf/avg_authtostart.pdf.

*** APPENDIX TABLES AND FIGURES – NOT FOR PUBLICATION ***

Appendix Table 1. Contemporaneous and Lagged Weather Effects on Employment Growth
Industry: Mining and Logging

	(1) Contemporaneous	(2) 1st lag	(3) 2nd lag	(4) 3rd lag	(5) Cumulative effect
Avg. daily high temp - Spring	0.364***	-0.162**	-0.194***	-0.184***	-0.176*
	(0.066)	(0.063)	(0.061)	(0.055)	(0.094)
Avg. daily high temp - Summer	-0.080	-0.151**	-0.178***	-0.181***	-0.591***
	(0.078)	(0.067)	(0.063)	(0.049)	(0.099)
Avg. daily high temp - Fall	0.064	0.085	-0.078	-0.037	0.034
	(0.050)	(0.066)	(0.065)	(0.073)	(0.097)
Avg. daily high temp - Winter	0.222***	-0.077	-0.101	-0.091	-0.047
	(0.064)	(0.066)	(0.072)	(0.078)	(0.125)
Precipitation (mm)	-0.115***	-0.008	0.060***	-0.044**	-0.108***
	(0.021)	(0.021)	(0.022)	(0.020)	(0.038)
Snowfall (cm)	-0.055**	-0.075***	-0.005	0.005	-0.130***
	(0.024)	(0.026)	(0.022)	(0.024)	(0.040)
% days high temp >90F	-0.001	-0.010	0.074*	0.014	0.076
	(0.043)	(0.043)	(0.044)	(0.042)	(0.066)
% days low temp <30F	0.095	-0.094	-0.112	-0.066	-0.178
	(0.091)	(0.095)	(0.096)	(0.080)	(0.147)
N	960372				
Counties	3108				
Months	309				
R2	0.346				

***p<0.01, **p<0.05, *p<0.10

Appendix Table 2. Contemporaneous and Lagged Weather Effects on Employment Growth
Industry: Construction

	(1) Contemporaneous	(2) 1st lag	(3) 2nd lag	(4) 3rd lag	(5) Cumulative effect
Avg. daily high temp - Spring	0.618***	-0.233***	-0.307***	-0.178***	-0.100
	(0.043)	(0.042)	(0.040)	(0.037)	(0.062)
Avg. daily high temp - Summer	0.166***	-0.138***	-0.143***	-0.128***	-0.243***
	(0.045)	(0.041)	(0.038)	(0.030)	(0.058)
Avg. daily high temp - Fall	0.164***	-0.083**	0.000	-0.041	0.041
	(0.033)	(0.041)	(0.045)	(0.045)	(0.067)
Avg. daily high temp - Winter	0.544***	-0.237***	-0.262***	-0.139***	-0.094
	(0.036)	(0.040)	(0.044)	(0.047)	(0.068)
Precipitation (mm)	-0.081***	0.127***	0.080***	0.031**	0.156***
	(0.013)	(0.014)	(0.014)	(0.013)	(0.024)
Snowfall (cm)	-0.119***	0.001	0.070***	0.003	-0.046*
	(0.016)	(0.016)	(0.015)	(0.014)	(0.024)
% days high temp >90F	-0.030	0.036	0.008	-0.005	0.009
	(0.028)	(0.028)	(0.027)	(0.029)	(0.044)
% days low temp <30F	-0.107**	-0.179***	0.086	0.027	-0.173**
	(0.051)	(0.055)	(0.055)	(0.051)	(0.087)
N	960372				
Counties	3108				
Months	309				
R2	0.479				

***p<0.01, **p<0.05, *p<0.10

Appendix Table 3. Contemporaneous and Lagged Weather Effects on Employment Growth
Industry: Manufacturing

	(1) Contemporaneous	(2) 1st lag	(3) 2nd lag	(4) 3rd lag	(5) Cumulative effect
Avg. daily high temp - Spring	0.060***	-0.019	-0.055***	0.016	0.002
	(0.014)	(0.013)	(0.014)	(0.013)	(0.019)
Avg. daily high temp - Summer	0.012	-0.004	0.027	0.005	0.039
	(0.024)	(0.020)	(0.018)	(0.016)	(0.029)
Avg. daily high temp - Fall	0.031*	-0.013	-0.012	0.009	0.015
	(0.016)	(0.019)	(0.022)	(0.022)	(0.031)
Avg. daily high temp - Winter	0.052***	-0.011	-0.007	-0.011	0.023
	(0.016)	(0.016)	(0.018)	(0.018)	(0.028)
Precipitation (mm)	-0.018***	-0.006	-0.007	0.003	-0.028***
	(0.005)	(0.006)	(0.006)	(0.006)	(0.010)
Snowfall (cm)	-0.011*	0.000	0.006	-0.002	-0.007
	(0.006)	(0.006)	(0.006)	(0.006)	(0.010)
% days high temp >90F	-0.025*	-0.007	-0.002	-0.041***	-0.075***
	(0.014)	(0.014)	(0.013)	(0.013)	(0.021)
% days low temp <30F	-0.007	-0.063***	0.003	0.008	-0.059*
	(0.021)	(0.022)	(0.022)	(0.020)	(0.035)
N	960372				
Counties	3108				
Months	309				
R2	0.294				

***p<0.01, **p<0.05, *p<0.10

Appendix Table 4. Contemporaneous and Lagged Weather Effects on Employment Growth
Industry: Utilities

	(1) Contemporaneous	(2) 1st lag	(3) 2nd lag	(4) 3rd lag	(5) Cumulative effect
Avg. daily high temp - Spring	0.059***	-0.024	0.024	-0.030	0.029
	(0.019)	(0.021)	(0.021)	(0.019)	(0.027)
Avg. daily high temp - Summer	0.004	-0.005	-0.036	0.019	-0.017
	(0.032)	(0.028)	(0.027)	(0.023)	(0.037)
Avg. daily high temp - Fall	0.043*	-0.030	-0.103***	0.025	-0.065
	(0.023)	(0.027)	(0.029)	(0.032)	(0.041)
Avg. daily high temp - Winter	0.021	-0.066**	-0.047*	-0.004	-0.096**
	(0.022)	(0.026)	(0.027)	(0.030)	(0.043)
Precipitation (mm)	-0.003	-0.001	-0.005	0.003	-0.007
	(0.008)	(0.009)	(0.008)	(0.009)	(0.015)
Snowfall (cm)	-0.004	0.008	-0.001	-0.006	-0.003
	(0.008)	(0.008)	(0.008)	(0.008)	(0.012)
% days high temp >90F	-0.011	-0.009	0.044**	-0.004	0.021
	(0.018)	(0.018)	(0.018)	(0.019)	(0.027)
% days low temp <30F	0.014	-0.010	0.054	0.007	0.064
	(0.031)	(0.035)	(0.033)	(0.029)	(0.053)
N	960372				
Counties	3108				
Months	309				
R2	0.245				

***p<0.01, **p<0.05, *p<0.10

Appendix Table 5. Contemporaneous and Lagged Weather Effects on Employment Growth
Industry: Retail Trade

	(1) Contemporaneous	(2) 1st lag	(3) 2nd lag	(4) 3rd lag	(5) Cumulative effect
Avg. daily high temp - Spring	0.082***	-0.012	-0.026**	-0.035***	0.009
	(0.012)	(0.011)	(0.011)	(0.010)	(0.014)
Avg. daily high temp - Summer	0.019	0.035**	-0.045***	0.004	0.013
	(0.018)	(0.016)	(0.014)	(0.011)	(0.020)
Avg. daily high temp - Fall	-0.023*	0.028*	-0.023	0.018	0.000
	(0.013)	(0.016)	(0.017)	(0.018)	(0.025)
Avg. daily high temp - Winter	0.002	0.001	-0.018	-0.009	-0.024
	(0.011)	(0.013)	(0.014)	(0.014)	(0.020)
Precipitation (mm)	-0.010**	0.007	0.018***	0.000	0.015*
	(0.004)	(0.005)	(0.005)	(0.004)	(0.008)
Snowfall (cm)	-0.017***	0.006	0.006	0.004	-0.001
	(0.004)	(0.005)	(0.004)	(0.005)	(0.007)
% days high temp >90F	-0.011	-0.012	-0.007	0.000	-0.030*
	(0.011)	(0.011)	(0.012)	(0.011)	(0.016)
% days low temp <30F	-0.038**	-0.028*	0.032*	-0.004	-0.039
	(0.017)	(0.017)	(0.017)	(0.015)	(0.025)
N	960372				
Counties	3108				
Months	309				
R2	0.467				

***p<0.01, **p<0.05, *p<0.10

Appendix Table 6. Contemporaneous and Lagged Weather Effects on Employment Growth
Industry: Transp. and Warehousing

	(1) Contemporaneous	(2) 1st lag	(3) 2nd lag	(4) 3rd lag	(5) Cumulative effect
Avg. daily high temp - Spring	0.140***	-0.068**	0.004	-0.028	0.048
	(0.030)	(0.028)	(0.028)	(0.027)	(0.040)
Avg. daily high temp - Summer	0.083*	-0.052	-0.063	-0.019	-0.051
	(0.048)	(0.040)	(0.038)	(0.036)	(0.058)
Avg. daily high temp - Fall	0.045	-0.010	-0.090**	0.009	-0.046
	(0.030)	(0.037)	(0.042)	(0.045)	(0.061)
Avg. daily high temp - Winter	0.084**	-0.147***	-0.067*	0.065	-0.066
	(0.033)	(0.039)	(0.038)	(0.041)	(0.058)
Precipitation (mm)	-0.046***	0.012	-0.003	0.003	-0.034
	(0.012)	(0.012)	(0.012)	(0.012)	(0.022)
Snowfall (cm)	-0.007	0.007	0.010	-0.008	0.003
	(0.012)	(0.012)	(0.013)	(0.012)	(0.021)
% days high temp >90F	-0.029	0.019	0.014	-0.042	-0.038
	(0.027)	(0.026)	(0.027)	(0.027)	(0.040)
% days low temp <30F	-0.016	-0.031	-0.050	0.084**	-0.013
	(0.047)	(0.050)	(0.050)	(0.042)	(0.076)
N	960372				
Counties	3108				
Months	309				
R2	0.380				

***p<0.01, **p<0.05, *p<0.10

Appendix Table 7. Contemporaneous and Lagged Weather Effects on Employment Growth
Industry: Information

	(1) Contemporaneous	(2) 1st lag	(3) 2nd lag	(4) 3rd lag	(5) Cumulative effect
Avg. daily high temp - Spring	-0.007	-0.002	-0.008	0.020	0.003
	(0.020)	(0.020)	(0.019)	(0.017)	(0.026)
Avg. daily high temp - Summer	0.105^{***}	0.037	-0.002	0.019	0.159^{***}
	(0.040)	(0.028)	(0.028)	(0.020)	(0.046)
Avg. daily high temp - Fall	-0.024	-0.072^{**}	-0.072^{**}	0.066^{*}	-0.101^{*}
	(0.024)	(0.034)	(0.035)	(0.035)	(0.059)
Avg. daily high temp - Winter	0.038	-0.024	-0.032	0.009	-0.010
	(0.024)	(0.027)	(0.029)	(0.029)	(0.041)
Precipitation (mm)	0.006	0.023^{**}	0.009	-0.007	0.031^{*}
	(0.010)	(0.010)	(0.009)	(0.010)	(0.017)
Snowfall (cm)	-0.008	-0.015^{*}	0.011	-0.003	-0.016
	(0.009)	(0.009)	(0.009)	(0.008)	(0.013)
% days high temp >90F	0.001	-0.056^{***}	0.021	-0.028	-0.062^{*}
	(0.022)	(0.021)	(0.022)	(0.022)	(0.034)
% days low temp <30F	-0.011	0.052	0.046	0.030	0.117^{**}
	(0.033)	(0.035)	(0.033)	(0.029)	(0.053)
N	960372				
Counties	3108				
Months	309				
R2	0.206				

***p<0.01, **p<0.05, *p<0.10

Appendix Table 8. Contemporaneous and Lagged Weather Effects on Employment Growth
Industry: Financial Activities

	(1) Contemporaneous	(2) 1st lag	(3) 2nd lag	(4) 3rd lag	(5) Cumulative effect
Avg. daily high temp - Spring	0.044^{***}	0.017	-0.004	-0.028^{**}	0.029^{*}
	(0.013)	(0.013)	(0.012)	(0.012)	(0.015)
Avg. daily high temp - Summer	0.036^{*}	-0.022	0.002	0.019	0.035
	(0.019)	(0.017)	(0.017)	(0.013)	(0.024)
Avg. daily high temp - Fall	0.002	-0.026	0.037^{**}	-0.005	0.008
	(0.014)	(0.018)	(0.019)	(0.018)	(0.026)
Avg. daily high temp - Winter	0.015	-0.004	-0.006	-0.008	-0.003
	(0.014)	(0.015)	(0.017)	(0.017)	(0.025)
Precipitation (mm)	-0.001	0.012^{**}	0.006	-0.006	0.011
	(0.005)	(0.005)	(0.005)	(0.005)	(0.009)
Snowfall (cm)	0.001	-0.001	0.003	0.003	0.006
	(0.005)	(0.006)	(0.005)	(0.005)	(0.007)
% days high temp >90F	-0.018	0.002	-0.018	-0.011	-0.045^{**}
	(0.012)	(0.012)	(0.012)	(0.011)	(0.018)
% days low temp <30F	0.009	0.021	0.014	-0.001	0.043
	(0.019)	(0.019)	(0.020)	(0.017)	(0.029)
N	960372				
Counties	3108				
Months	309				
R2	0.275				

***p<0.01, **p<0.05, *p<0.10

Appendix Table 9. Contemporaneous and Lagged Weather Effects on Employment Growth
Industry: Prof. and Bus. Serv.

	(1) Contemporaneous	(2) 1st lag	(3) 2nd lag	(4) 3rd lag	(5) Cumulative effect
Avg. daily high temp - Spring	0.149***	-0.068***	-0.058***	-0.049**	-0.025
	(0.023)	(0.024)	(0.022)	(0.021)	(0.033)
Avg. daily high temp - Summer	0.025	-0.029	-0.039	-0.023	-0.065
	(0.036)	(0.030)	(0.027)	(0.023)	(0.042)
Avg. daily high temp - Fall	-0.048*	0.055*	-0.010	0.070**	0.068
	(0.025)	(0.032)	(0.034)	(0.035)	(0.049)
Avg. daily high temp - Winter	0.064**	-0.040	-0.057*	-0.062*	-0.095*
	(0.029)	(0.030)	(0.034)	(0.035)	(0.051)
Precipitation (mm)	-0.020**	0.020*	0.017*	0.005	0.022
	(0.010)	(0.010)	(0.009)	(0.010)	(0.018)
Snowfall (cm)	-0.039***	0.014	0.014	-0.005	-0.017
	(0.010)	(0.010)	(0.009)	(0.010)	(0.015)
% days high temp >90F	0.022	-0.033	-0.002	-0.033	-0.047
	(0.022)	(0.022)	(0.023)	(0.023)	(0.034)
% days low temp <30F	-0.052	-0.028	0.002	0.004	-0.074
	(0.038)	(0.040)	(0.040)	(0.034)	(0.064)
N	960372				
Counties	3108				
Months	309				
R2	0.281				

***p<0.01, **p<0.05, *p<0.10

Appendix Table 10. Contemporaneous and Lagged Weather Effects on Employment Growth
Industry: Edu. and Health Serv.

	(1) Contemporaneous	(2) 1st lag	(3) 2nd lag	(4) 3rd lag	(5) Cumulative effect
Avg. daily high temp - Spring	0.017	-0.002	-0.004	-0.011	0.000
	(0.011)	(0.011)	(0.010)	(0.010)	(0.014)
Avg. daily high temp - Summer	0.036*	-0.018	-0.003	0.016	0.031
	(0.020)	(0.017)	(0.016)	(0.013)	(0.021)
Avg. daily high temp - Fall	-0.014	-0.006	0.010	0.020	0.010
	(0.012)	(0.015)	(0.018)	(0.017)	(0.025)
Avg. daily high temp - Winter	0.004	0.005	0.006	0.007	0.021
	(0.015)	(0.015)	(0.017)	(0.017)	(0.025)
Precipitation (mm)	-0.005	0.006	0.001	0.005	0.007
	(0.005)	(0.005)	(0.005)	(0.005)	(0.009)
Snowfall (cm)	-0.023***	0.011*	0.014***	-0.004	-0.001
	(0.005)	(0.006)	(0.004)	(0.004)	(0.007)
% days high temp >90F	-0.002	-0.013	0.005	-0.019*	-0.028
	(0.012)	(0.012)	(0.012)	(0.011)	(0.019)
% days low temp <30F	0.028	-0.004	-0.007	0.013	0.029
	(0.022)	(0.018)	(0.019)	(0.017)	(0.028)
N	960372				
Counties	3108				
Months	309				
R2	0.277				

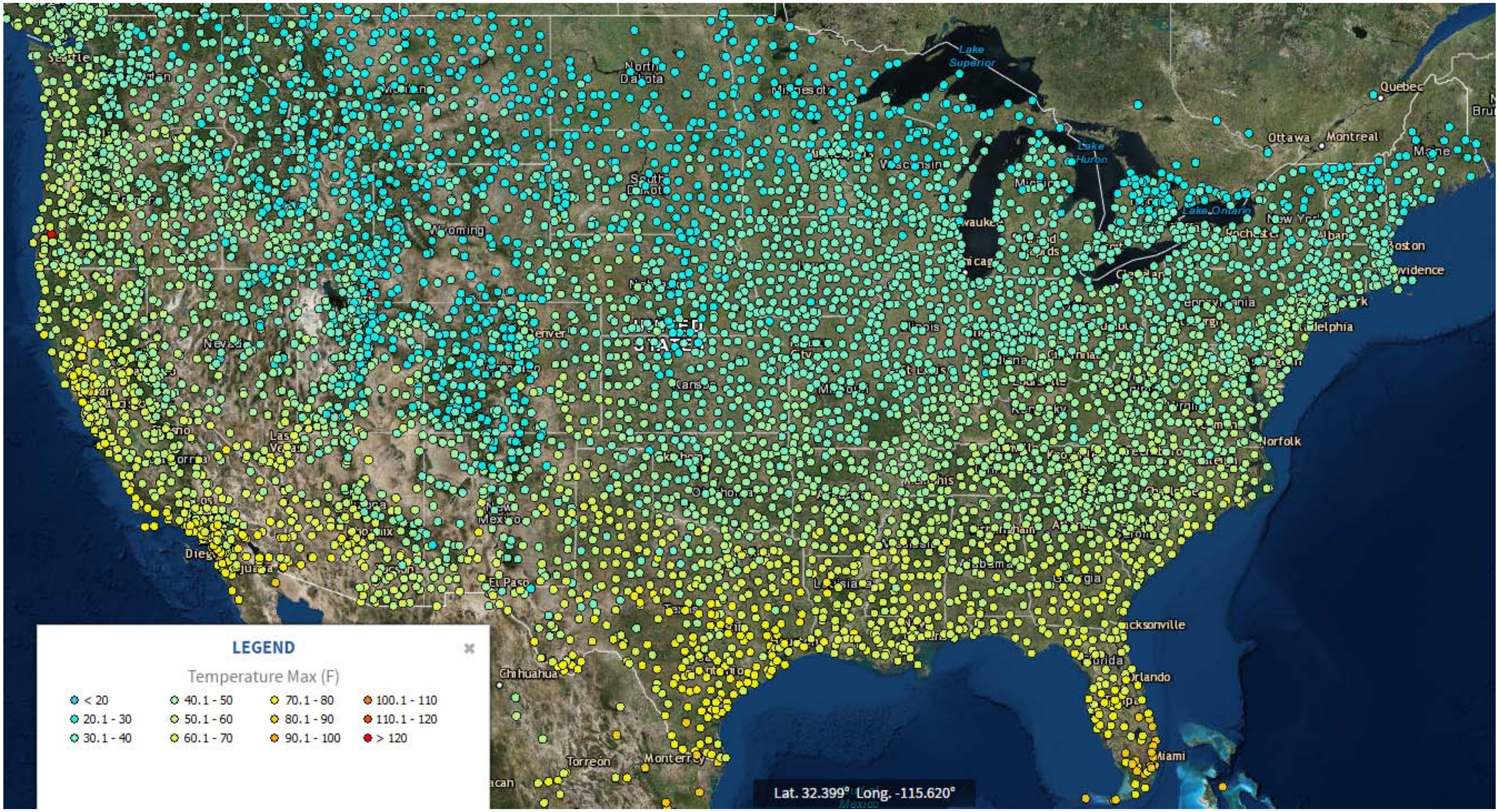
***p<0.01, **p<0.05, *p<0.10

Appendix Table 11. Contemporaneous and Lagged Weather Effects on Employment Growth
Industry: Leisure and Hosp.

	(1) Contemporaneous	(2) 1st lag	(3) 2nd lag	(4) 3rd lag	(5) Cumulative effect
Avg. daily high temp - Spring	0.183***	-0.040*	-0.057***	-0.065***	0.022
	(0.020)	(0.021)	(0.020)	(0.020)	(0.029)
Avg. daily high temp - Summer	0.170***	-0.086***	-0.056**	0.042**	0.069**
	(0.028)	(0.024)	(0.024)	(0.020)	(0.035)
Avg. daily high temp - Fall	0.048**	-0.014	-0.038	0.002	-0.001
	(0.021)	(0.028)	(0.029)	(0.030)	(0.040)
Avg. daily high temp - Winter	0.099***	0.011	-0.052**	-0.033	0.025
	(0.020)	(0.023)	(0.024)	(0.026)	(0.034)
Precipitation (mm)	-0.027***	0.029***	0.013	-0.002	0.013
	(0.008)	(0.008)	(0.008)	(0.008)	(0.014)
Snowfall (cm)	-0.027***	0.010	0.001	-0.001	-0.016
	(0.008)	(0.009)	(0.008)	(0.007)	(0.011)
% days high temp >90F	-0.052***	0.006	-0.037**	0.011	-0.072***
	(0.018)	(0.020)	(0.019)	(0.018)	(0.028)
% days low temp <30F	-0.108***	-0.039	0.069**	0.046	-0.032
	(0.030)	(0.030)	(0.030)	(0.028)	(0.044)
N	960372				
Counties	3108				
Months	309				
R2	0.615				

***p<0.01, **p<0.05, *p<0.10

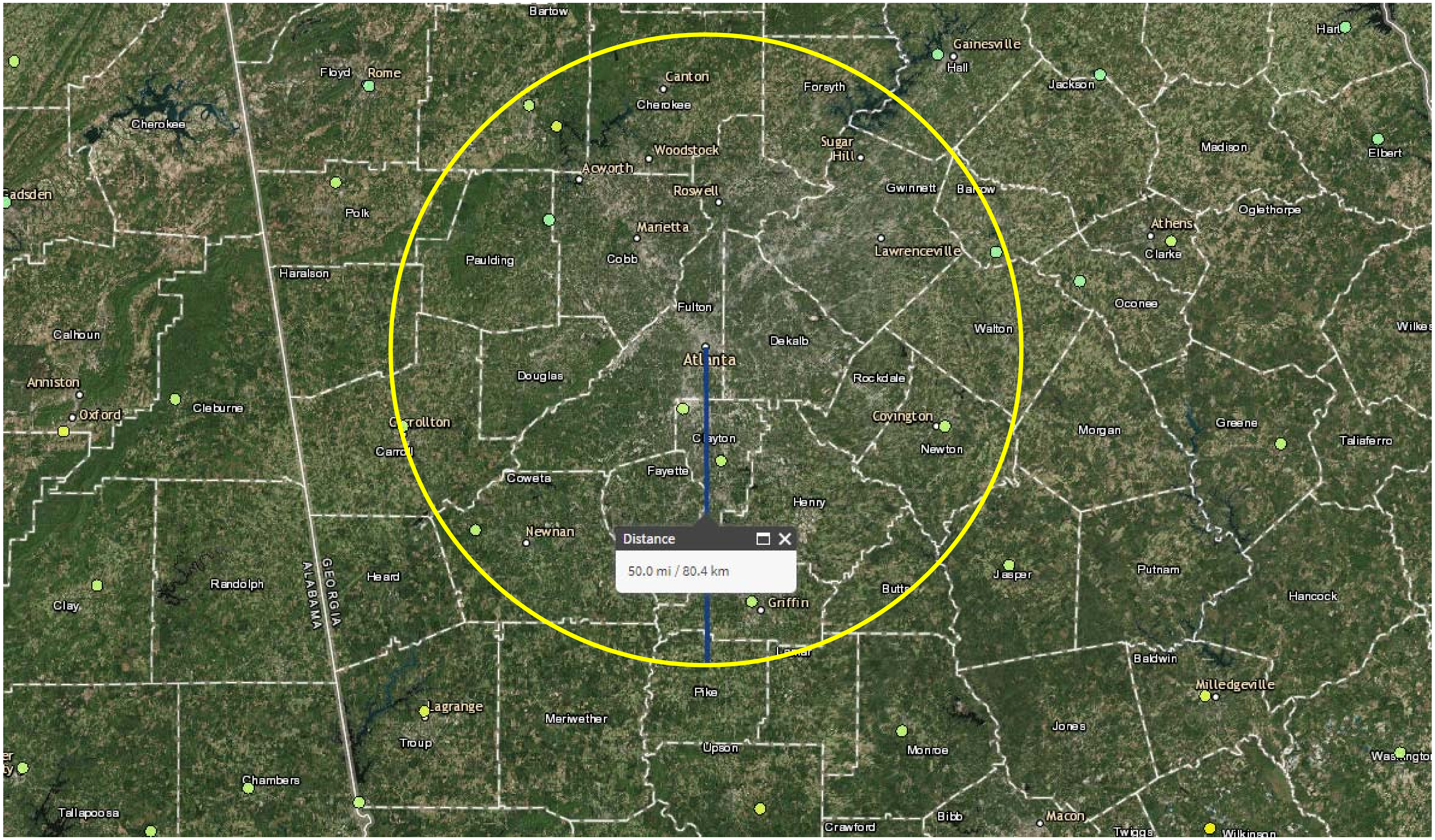
Online Appendix Figure 1
Map of Locations of U.S. GHCN-Daily Weather Stations as of January 1, 2006



Source: https://gis.ncdc.noaa.gov/maps/ncei/summaries/daily.

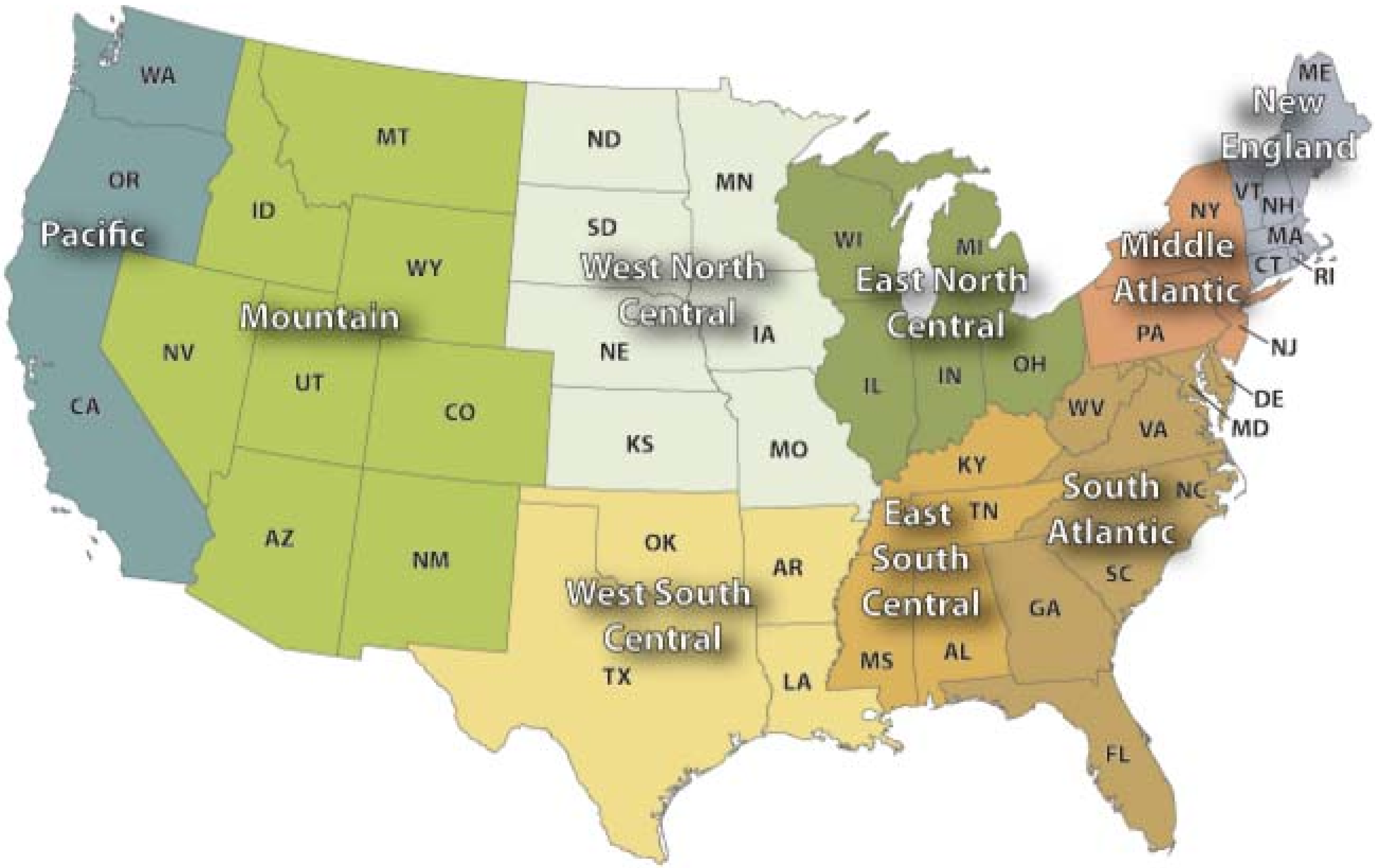
Online Appendix Figure 2

Map of Locations of GHCN-Daily Weather Stations near Atlanta, GA as of January 1, 2006

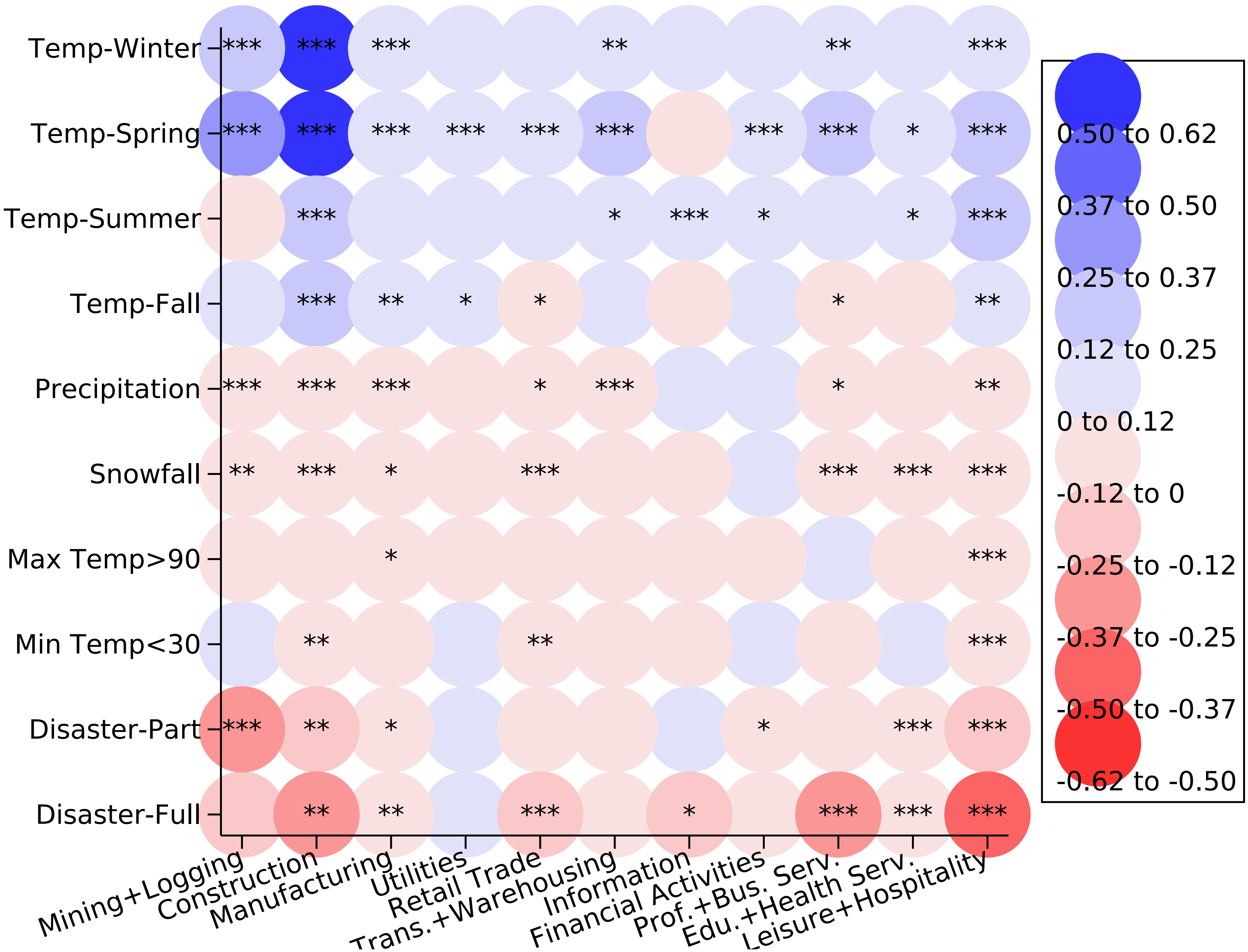


Source: https://gis.ncdc.noaa.gov/maps/ncei/summaries/daily.

Online Appendix Figure 3
Map of Census Divisions

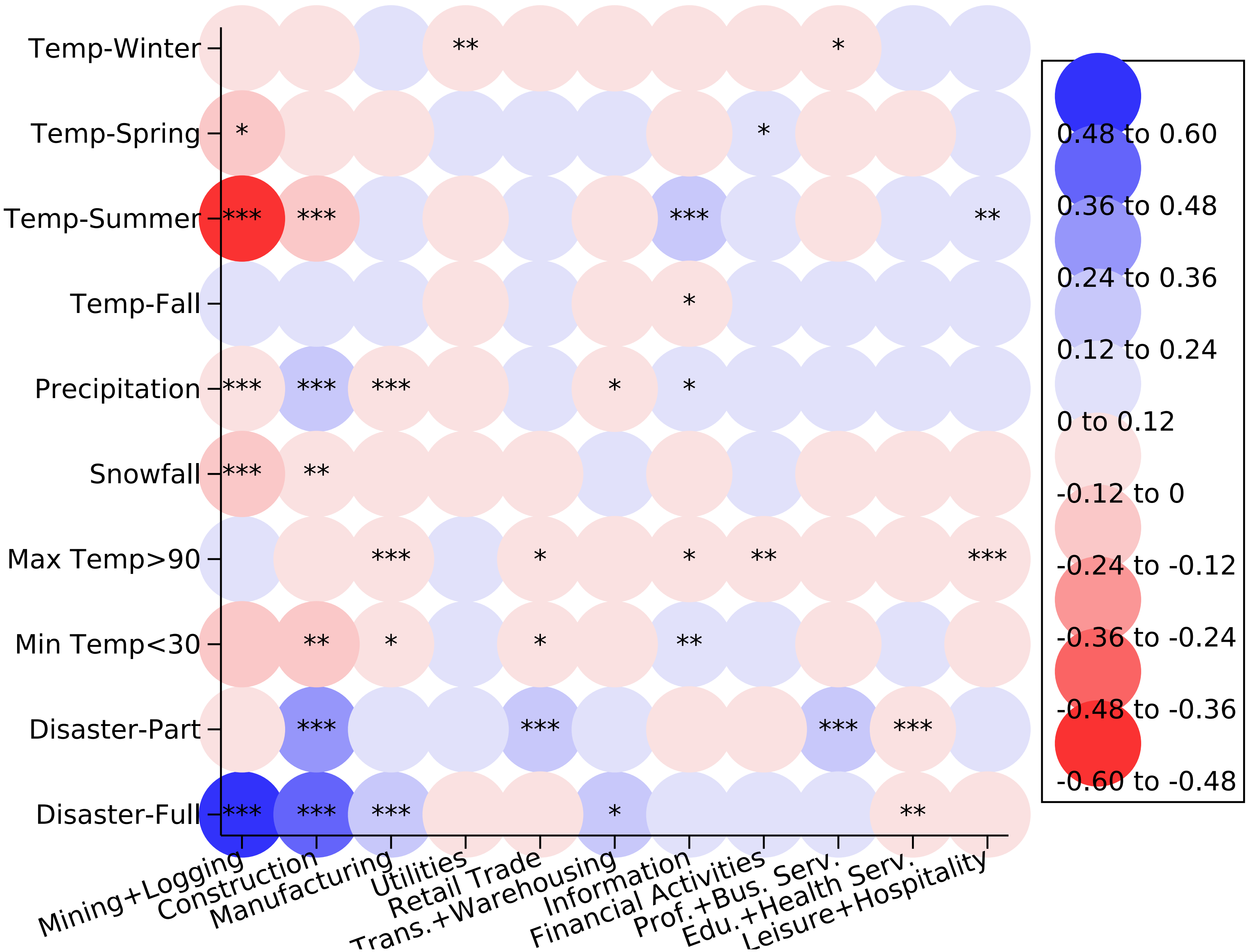


Appendix Figure 4. Heatmap of Contemporaneous Weather Effects By Industry, Including Disasters



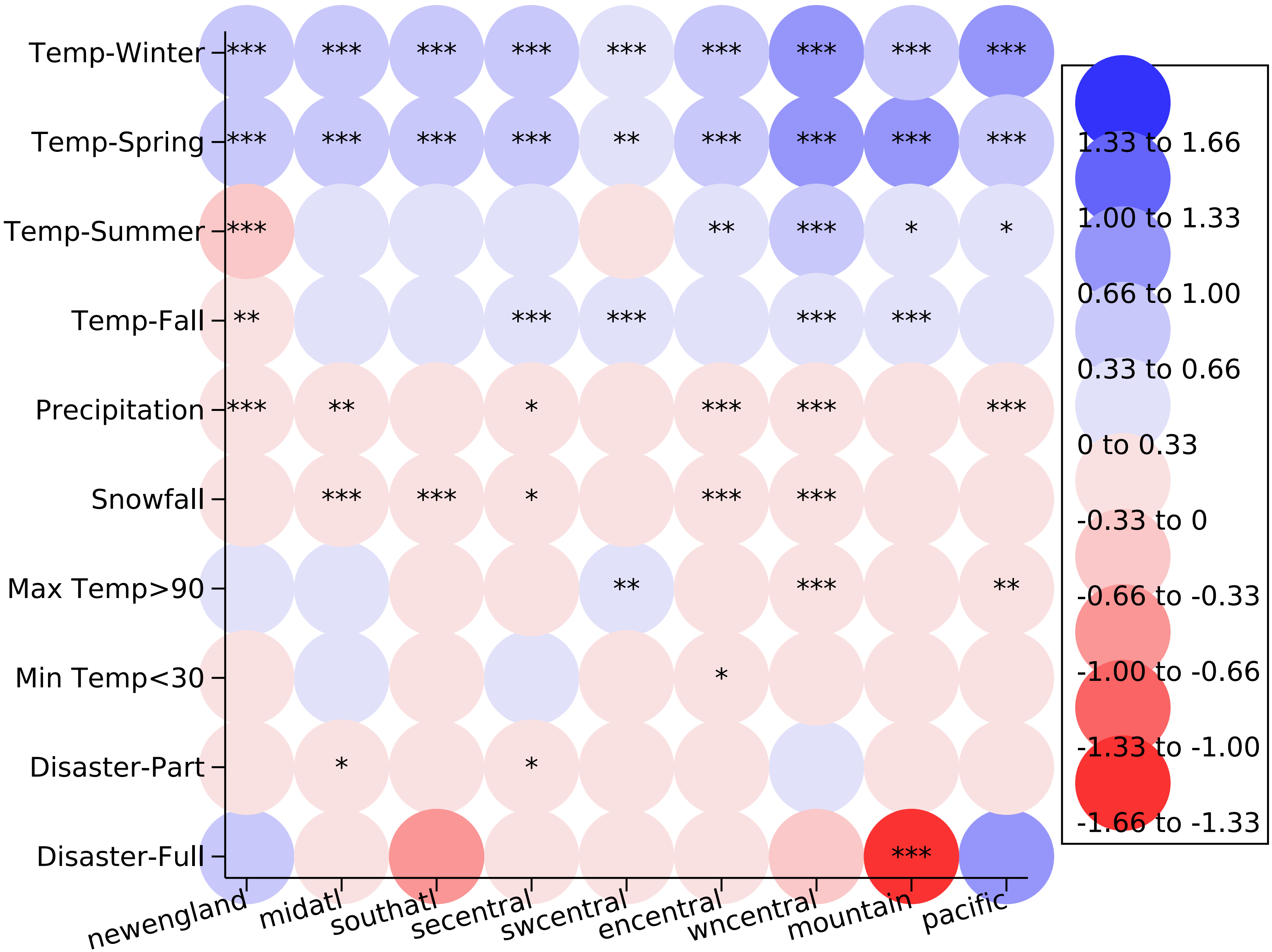
Notes: Each cell of heatmap above represents the coefficient on the weather variable indicated on the y-axis on employment growth in the industry indicated on the x-axis. Positive values are shown as blue circles, while negative values are shown as red, with darker shading for larger (in absolute values) coefficients. The stars indicate statistical significance: ***p<.01, ** p<.05, * p<.10

Appendix Figure 5. Heatmap of Cumulative Weather Effects By Industry, Including Disasters



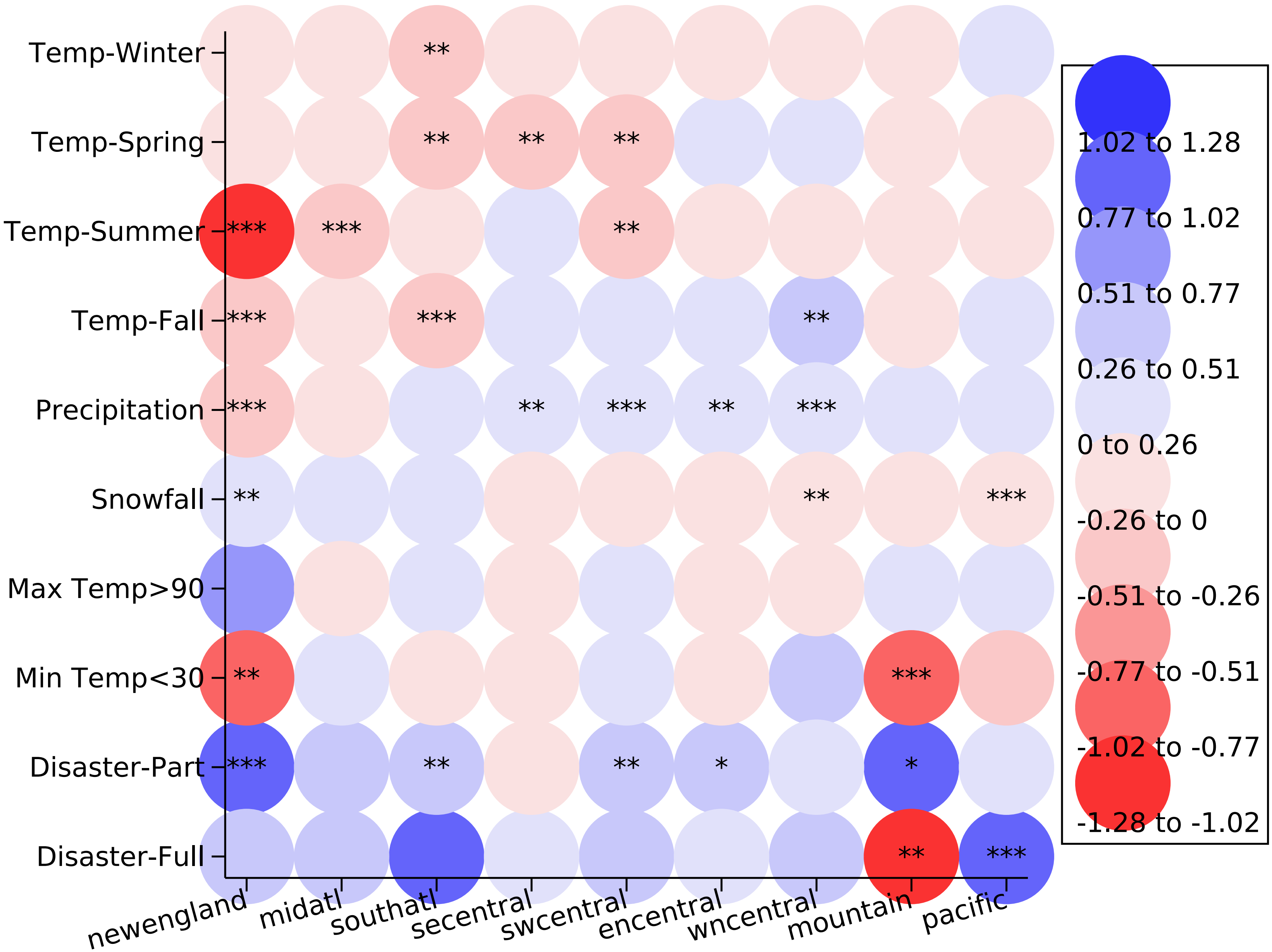
Notes: Each cell of heatmap above represents the coefficient on the weather variable indicated on the y-axis on employment growth in the industry indicated on the x-axis. Positive values are shown as blue circles, while negative values are shown as red, with darker shading for larger (in absolute values) coefficients. The stars indicate statistical significance: ***p<.01, ** p<.05, * p<.10

Appendix Figure 6. Heatmap of Contemporaneous Weather Effects By Region on Construction



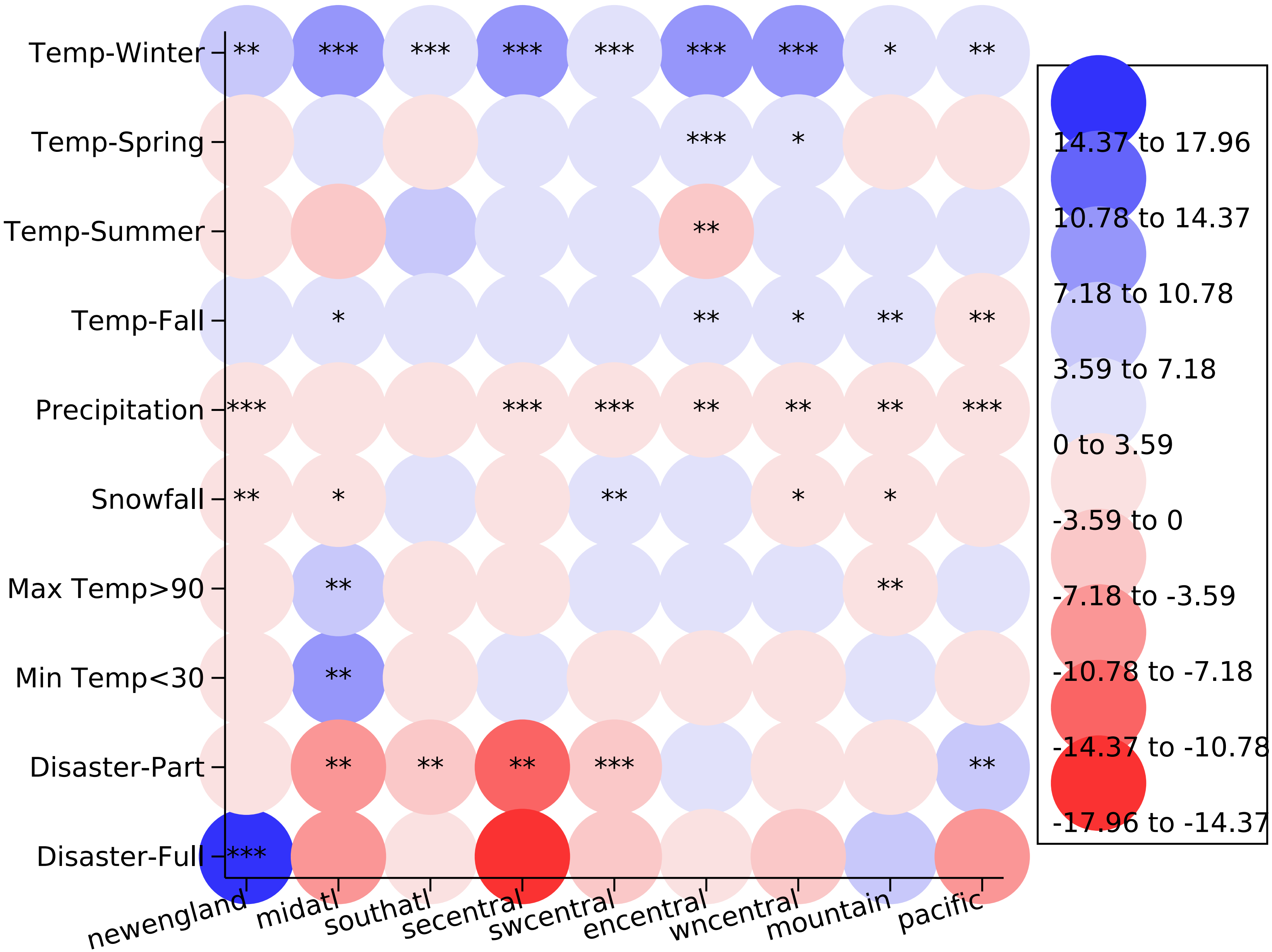
Notes: Each cell of heatmap above represents the coefficient on the weather variable indicated on the y-axis on construction growth in the industry indicated on the x-axis. Positive values are shown as blue circles, while negative values are shown as red, with darker shading for larger (in absolute values) coefficients. The stars indicate statistical significance: ***p<.01, ** p<.05, * p<.10

Appendix Figure 7. Heatmap of Cumulative Weather Effects By Region on Construction



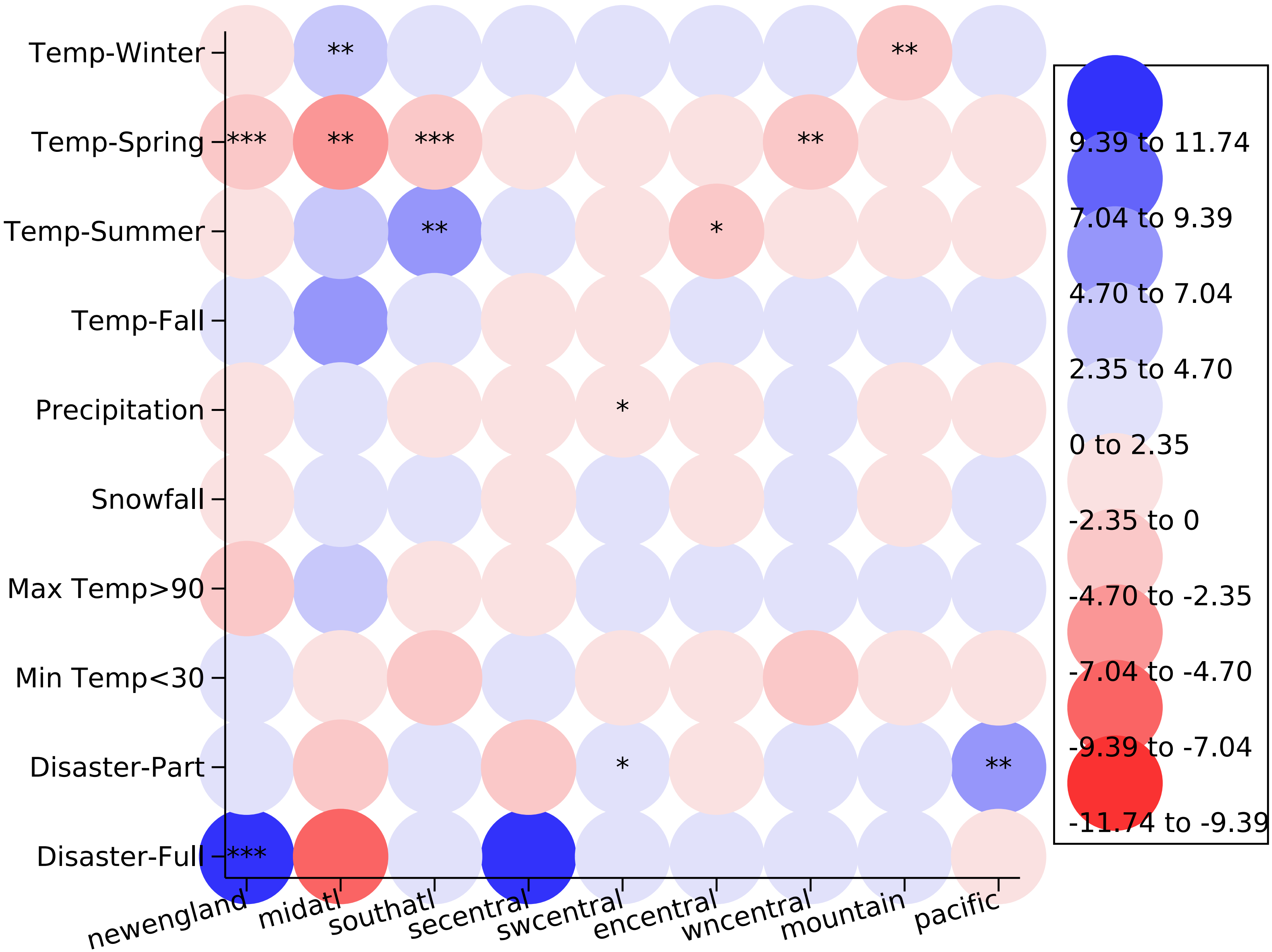
Notes: Each cell of heatmap above represents the coefficient on the weather variable indicated on the y-axis on construction growth in the industry indicated on the x-axis. Positive values are shown as blue circles, while negative values are shown as red, with darker shading for larger (in absolute values) coefficients. The stars indicate statistical significance: ***p<.01, ** p<.05, * p<.10

Appendix Figure 8. Heatmap of Contemporaneous Weather Effects By Region on Building Permits



Notes: Each cell of heatmap above represents the coefficient on the weather variable indicated on the y-axis on building permit growth in the industry indicated on the x-axis. Positive values are shown as blue circles, while negative values are shown as red, with darker shading for larger (in absolute values) coefficients. The stars indicate statistical significance: ***p<.01, ** p<.05, * p<.10

Appendix Figure 9. Heatmap of Cumulative Weather Effects By Region on Building Permits



Notes: Each cell of heatmap above represents the coefficient on the weather variable indicated on the y-axis on building permit growth in the industry indicated on the x-axis. Positive values are shown as blue circles, while negative values are shown as red, with darker shading for larger (in absolute values) coefficients. The stars indicate statistical significance: ***p<.01, ** p<.05, * p<.10