MOVING TO NICE WEATHER

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Abstract

U.S. residents, both old and young, have been moving en masse to places with nice weather. Well known is the migration towards places with warmer winter weather, which is often attributed to the introduction of air conditioning. But people have also been moving to places with cooler and less-humid summer weather, which is the opposite of what would be expected from the introduction of air conditioning. Empirical evidence suggests that the main force driving weather-related moves is an increasing valuation of weather's contribution to quality of life. Cross-sectional population growth regressions are able to achieve a relatively good match with an a priori ranking of the weather's contribution to local quality of life.

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1 Introduction

Over the course of the twentieth century, U.S. residents moved in mass to places with nice weather. Well known is the migration towards places with warm winter weather, which is often attributed to the introduction of air conditioning (Oi, 1997). But people have also been moving to places with cooler, less-humid summer weather, which is the opposite of what would be expected from the introduction of air conditioning. The latter trend suggests that a large portion of weather-related moves are due to individuals' having increased their valuation of the weather's contribution to their quality of life, probably due to broad-based rising real incomes (Glaeser, Kolko, Saiz, 2001). If so, individuals are likely to have increased their valuation of other local quality-of-life attributes as well.

Valuing weather's contribution to quality of life has received considerable attention in the compensating differential literature. The value of a characteristic is calculated as the sum of the wages an individual is willing to forego plus the house price premium an individual is willing to pay to live in a metropolitan area with a given weather characteristic (Rosen, 1979; Roback, 1982). Based on public use microsamples from the 1980 decennial census, one hundred fewer annual heating degree days are estimated to be valued (in 2002 dollars) from \$5 to \$40 per household; one hundred less annual cooling degree days are estimated to be valued from \$2 to \$218 per household; one extra sunny day per year, from \$19 to \$33 per household; one inch less precipitation, from -\$58 to \$34 (Blomquist, Berger, and Hoen, 1988; Gyourko and Tracy, 1991; and Stover and Leven, 1992). A limitation of the compensating differential literature is that the number of geographic observations is relatively small; the above estimates are based on cross-sections of either 253 urban counties or 130 metropolitan areas. Moreover, there is a sharp selection bias in that only places where large numbers of people have chosen to live are included in the sample.

The alternative approach pursued herein is to describe the partial correlations between population density and detailed measures of weather for the more than 3,000 continental U.S. counties. Both population density and its growth rate are characterized by robust inverse partial correlations with various measures of cold winter weather and hot summer weather. Population *density* is additionally characterized by a quantitatively small inverse partial correlation with annual precipitation. Population *growth* is additionally characterized by a strong inverse partial correlation with summer humidity. Moreover, sparse regression specifications using just a few weather elements have extremely high explanatory power in accounting for the variation in both population density and population growth.

The paper proceeds as follows. Section 2 reviews the theoretical justification for using population density and its growth rate to measure local economic performance; it then suggests some obvious ways in which weather affects local welfare and how such contributions may have changed over the twentieth century. Section 3 formally lays out an econometric specification for estimating local attributes' contribution to local welfare. Section 4 describes the data used in the estimation. Section 5 presents results on the univariate and partial correlations between population density and a variety of elements measuring winter weather, summer weather, and annual precipitation. Section 6 does the same for the growth of population density and then argues that these partial correlations suggest that a large portion of weather-motivated migration is driven by broad-based technological progress rather than the specific technological innovation of air conditioning or life-cycle motivated elderly migration. Section 7 compares weather's expected contribution to welfare as predicted by the population density and population growth regressions with an a priori quality-of-life index of weather; it concludes that cross-sectional population growth regressions successfully capture changes in contributions to local welfare. A last section briefly concludes.

2 Theory and Predictions

What are the contributions from various local attributes to the welfare of local residents? Thinking of a "locality" as a geographic area where people both live and work, a first mechanism by which local attributes impact local welfare is by affecting the productivity of local firms. With competitive local labor markets, higher firm productivity puts upward pressure on local wages, in turn allowing residents to increase their consumption of goods and services. Alternatively, local attributes may themselves be directly valued by residents, in which case they affect local "quality of life" (Rosen, 1979; Roback, 1982).

Neither local welfare nor its determinants, local productivity and local quality of life, are directly observable. But in a system of many localities among which there is high mobility, the movement of firms seeking higher profits and the movement of individuals seeking higher utility induces positive correlations between local population density and each of local productivity and local quality of life, $\frac{\partial L}{\partial(\text{productivity})} > 0$ and $\frac{\partial L}{\partial(\text{quality-of-life})} > 0$ (Haurin, 1980; Glaeser et al., 1992, 1995; Ciccone and Hall, 1996; Rappaport, 1999, 2003; Rappaport and Sachs, 2003).[1] Consistent with the idea that people vote with their feet (Tiebout, 1956), population density reveals individuals' preferences over local areas by aggregating the indirect contribution to welfare via productivity-driven higher wages with the direct contribution to welfare via high quality of life. Inherent in such aggregation is that population density cannot distinguish between the two mechanisms.

Weather stands out as an obvious local attribute affecting local productivity and local quality of life. Consider winter and summer temperature. Extreme cold and heat can kill; they cause considerable discomfort; they cause machines to fail; they run up energy bills. Extreme cold freezes pipes. Extreme heat spoils food and slows thoughts and activities. So controlling for summer temperature, population density should be positively correlated with winter temperature; controlling for winter temperature, population density should be negatively correlated with summer temperature (Table 1, Row 1).

If population density measures the contribution of local attributes to local welfare via productivity and quality of life, its growth rate measures the *change* in such contributions. A first reason to believe the contribution from weather to local welfare has changed over the past century is the invention and spread of air conditioning and other weather-ameliorating technologies. A second reason is the possibility that rising incomes have increased demand for local quality-of-life attributes such as nice weather.

The introduction of air conditioning (AC), the mechanical dehumidification and cool-

[1] The proofs in Rappaport (1999) and Rappaport and Sachs (2003) that $\frac{\partial L}{\partial(\text{productivity})} > 0$ rely on the exclusion of land from production. With land as a productive input, the derivative can go in the other direction. But Rappaport (2003) shows this to occur only under extreme circumstances.

ing of indoor environments, can be dated to about 1899. In that year, Cornell Medical College installed a custom-designed refrigeration unit to cool the air of one of its dissecting laboratories. A few key patents during the years 1904 to 1907 facilitated the spread of custom-designed AC units to manufacturers of products requiring constant, low humidity. Such products included gunpowder, macaroni, tobacco, gum, and chocolate. Starting in 1917, premier movie theaters began installing AC as a way to attract patrons during hot and humid summers. During the 1920s, air conditioning companies increasingly marketed AC to a wide range of manufacturing companies as a way of raising the productivity of factory workers, whose efforts might otherwise falter in hot, sweltering conditions.[2] (Edwards, 1994; Cooper, 1998; Ackerman, 2002)

The mass adoption of residential air conditioning did not take place until after World War II. It was made possible by the invention of the low-pressure refrigerant freon in 1930. But as late as 1960, residential air conditioning remained relatively scarce. Only 12.5 percent of U.S. households had any sort of AC in 1960; only 1.9 percent had central AC; and indeed only 4.7 percent of housing units constructed between 1950 and 1960 had central AC (Supplemental Table 1). Even in sweltering Texas, only 11.6 percent of housing units constructed between 1950 and 1960 included central AC. By 1980, residential air conditioning was relatively common. 56.2 percent of households had some sort of AC in 1980; 27.8 percent had central AC; and 52.7 percent of housing units constructed between 1970 and 1980 had central AC, including 85.0 percent of newly constructed units in Texas.[3]

The invention and spread of air conditioning was a clear technological shock that made locations with hot summer weather less unpleasant places to live and more productive places to work. Individuals' willingness to pay for the absence of hot summer weather should have decreased. And firms in places with hot summer weather should have been able to increase their wages. Both of these results would induce migration toward places with warm summers. In other words, all else equal (including winter temperature), the expected partial

[2] Oi (1997) presents evidence that AC indeed raises worker productivity.

[3] Correspondingly, the first mass production automobile air-conditioner was introduced in 1954. Factory installed AC rose from 10 percent of new cars sold in the U.S. in 1965 to 81 percent of new cars in 1983 to 92 percent in 1990 (Motor Vehicle Manufacturers Association, 1991; AutomobileIndia.com, 2003).

correlation of population growth with summer temperature is positive (Table 1, Row 3). Because summer and winter temperatures are positively correlated, migration towards places with warm summers implies migration away from places with cold winters. So not controlling for summer temperature, the expected raw correlation of growth with winter temperature is positive. The seasonal correlation of weather further implies that air conditioning lowered the cost of escaping from cold winters. The hot summers associated with doing so were no longer quite so insufferable. Thus the required compensation for enduring cold winters should have increased. So even after controlling for summer weather, the introduction of air conditioning predicts a positive partial correlation of growth with winter temperature.

As the spread of air conditioning was ameliorating living with hot summer weather, other technological changes were ameliorating living with cold winter weather. Central home heating gradually replaced room heating during the latter part of the nineteenth century (Doyle, 2003). Early furnaces were mostly fired by coal, which remained the primary home heating fuel as late as 1950. Coal required frequent home deliveries, large storage spaces, and the disposal of large quantities of soot. Furnaces needed to be manually fed throughout the day and produced high indoor air pollution, including a foul-smelling sulfur odor and the significant potential for carbon monoxide poisoning (Matthews, 2001). Oil started to replace coal as a source of home heating during the 1920s and had surpassed it by 1960. Oil was much more convenient than coal. But it still required frequent home deliveries, and many oil-fired furnaces continued to produce considerable soot and other indoor air pollution. More recently, utility-supplied natural gas and electricity have become the primary fuels heating U.S. homes. From heating just 11 percent of U.S. homes in 1940, they together grew to heat 82 percent of U.S. homes in 2000 (Supplemental Table 2). Natural gas and electricity offer the convenience of automatic supply and cause much less indoor air pollution than early oil-fired furnaces.

Technological improvements in heating have made locations with cold winter weather less unpleasant places to live. Individuals' willingness to pay for the absence of cold winter weather should have decreased, thereby inducing some internal migration towards places with cold winters. All else equal (including summer weather), the resulting expected partial correlation of population growth with winter temperature is negative (Table 1, Row 4). The seasonal correlation of weather then implies a negative expected raw correlation of growth with summer temperature. Furthermore, improved heating technology lowered the cost of escaping from hot summers. Thus even after controlling for winter weather, the resulting partial correlation of growth with summer temperature is expected to be negative.

A completely different force changing the contribution of weather to individuals' quality of life has been the sharp increase in income and wealth driven by broad-based technological progress. National income accounts suggest that U.S. real per capita income rose more than sixfold during the twentieth century (Maddison, 1995). If anything, such an increase understates the actual rise in purchasing power, due to the difficulty of pricing major innovations diffused during the twentieth century, including residential electricity, safe drinking water, automobile travel, air travel, radio, television, personal computers, the internet, and continual breakthroughs in medical care (Nordhuas, 1997; Gordon, 2000).

Rising incomes should have raised individuals' marginal utility from the consumption of fixed-quantity local quality-of-life goods relative to their marginal utility from the consumption of produced goods. Unless the price premium to living in places with high quality of life rose proportional to the rise in income, internal migration towards such places should have taken place. The general equilibrium condition for such a migration is that the elasticity of substitution between consumption of produced goods and consumption of quality-of-life goods be less than unitary (Rappaport, 2003). With a less than unitary elasticity of substitution, the share of potential income that individuals devote to quality of life — through higher housing prices and lower wages — rises with technological progress.

Two empirical facts suggest that the elasticity of substitution between consumption of produced goods and consumption of quality of life is indeed likely to be less than one. First is that the elasticity of substitution between produced goods and leisure appears to be less than one. Evidence for this is the rising amount of time U.S. residents spend on leisure activities. Among employed U.S. males aged eighteen to sixty-four, total annual hours spent at work (including commute time and work breaks) declined by 17 percent between 1965 and 1985. And the retirement rate for men sixty-five years of age or older rose from 35 percent in 1900 to 83 percent in 1990, even as life expectancy at age sixty-five has greatly increased (Costa, 1998). Second is that elasticity of substitution between produced tradable goods and housing also appears to be less than one. With more rapid technological progress in the production of tradable goods, a less than unitary elasticity of substitution implies a rising share of consumption expenditures will be spent on housing (Baumol, 1967). In fact, the share of U.S. families' total expenditures devoted to housing rose from 11 percent in 1950 to 18 percent in 1991 (Costa, 1998).

Numerous weather elements other than winter and summer temperature are also likely to affect local welfare. The main additional ones included in the empirics below measure rain and snow. The expected partial correlations of population density with these are unclear. Rain and snow serve as sources of drinking water. Rain waters gardens and crops and helps prevent forest fires. Snow serves as a source of outdoor recreation. But rain also cancels outdoor recreation. And snow snarls traffic. A technological shock that suggests that places with less precipitation should have grown faster is improved large-scale construction technology developed during the early-to-mid twentieth century. This allowed the building of massive projects to move water to places that lacked it. An increasing demand for nice weather as a source of quality of life should also have caused places with less precipitation to have grown faster.

3 Econometric Specification

Based on the theory that local population density reflects underlying productivity and quality-of-life attributes, the assumed data-generating process is that steady-state population is a time-varying linear function of time-invariant local attributes (Glaeser et al., 1992, 1995; Rappaport, 1999; Rappaport and Sachs, 2003).

$$\mathbf{L}_t^* = \mathbf{X}\boldsymbol{\beta}_t \; + \; \boldsymbol{\upsilon}_t \tag{1}$$

The vector $\mathbf{L}_t^*$ is the natural log of steady-state population density for each of n localities. The n-by-k matrix $\mathbf{X}$ stacks measures of local weather along with correlated geography attributes such as coastal proximity and topography. The exogenous nature of these attributes eliminates a reverse-causal interpretation of partial correlations. A unitary column vector is also included in $\mathbf{X}$ to pick up a time-specific intercept. The disturbance term, $\boldsymbol{\upsilon}_t$, is assumed to have expectation zero and to be uncorrelated with $\mathbf{X}$.

Observed highly persistent local growth rates suggest that population adjusts slowly towards its steady state (Rappaport, 2002). Current population density thus proxies for unobservable steady-state density.

$$\mathbf{L}_t = \mathbf{X}\boldsymbol{\beta}_t \; + \; \underbrace{\boldsymbol{\upsilon}_t + (\mathbf{L}_t - \mathbf{L}_t^*)}_{\text{disturbance term}} \tag{2a}$$

The difference between steady-state and current population density gets subsumed in the disturbance term. This difference will in general be correlated with $\mathbf{X}$, thereby biasing estimates of $\boldsymbol{\beta}_t$. To illustrate, suppose that population density was at its steady state in the recent or more distant past after which there was a once-and-for-all structural shift from $\boldsymbol{\beta}_{t-\tau}$ to $\boldsymbol{\beta}_t$. Omitting disturbance terms, $\mathbf{L}_s = \mathbf{L}_s^* = \mathbf{L}_{t-\tau}^* = \mathbf{X}\boldsymbol{\beta}_{t-\tau}$ for $s \leq t - \tau$ and $\mathbf{L}_s^* = \mathbf{L}_t^* = \mathbf{X}\boldsymbol{\beta}_t$ for $t-\tau < s \leq t$. Additionally, let the speed at which log population density closes the gap to its steady state be a deterministic linear function of the log distance to its steady state, $\frac{\mathrm{d}}{\mathrm{d}t}(\mathbf{L}_t - \mathbf{L}_t^*) = -\lambda\,(\mathbf{L}_t - \mathbf{L}_t^*)$ with $\lambda > 0$. Solving the convergence differential equation and substituting gives

$$\begin{aligned} \mathbf{L}_t \;&=\; \left(1 - e^{-\lambda\tau}\right)\mathbf{L}_t^* \;+\; e^{-\lambda\tau}\mathbf{L}_{t-\tau}^* \\ &=\; \mathbf{X}\,\left(\left(1 - e^{-\lambda\tau}\right)\boldsymbol{\beta}_t + e^{-\lambda\tau}\boldsymbol{\beta}_{t-\tau}\right) \;+\; \underbrace{\left(1 - e^{-\lambda\tau}\right)\boldsymbol{\upsilon}_t + e^{-\lambda\tau}\boldsymbol{\upsilon}_{t-\tau}}_{\text{disturbance term}} \end{aligned} \tag{2b}$$

The disturbance term has expectation zero and is uncorrelated with $\mathbf{X}$. The assumptions yielding (2b) thus allow for unbiased estimates of a convex additive combination of $\boldsymbol{\beta}_t$ and $\boldsymbol{\beta}_{t-\tau}$. Intuitively, coefficients on the time-invariant attributes describe a combination of current and past steady-state relationships.[4]

A benefit of extended transitions is that they allow estimates of the direction of change

[4] If (4) below is the true data-generating process, coefficients on $\mathbf{X}$ from estimating (2a) and (2b) would still be interpreted as capturing a convex combination of past and present contributions to welfare.

in structural parameters, even well after such changes have occurred. Differencing (2a) gives

$$\mathbf{L}_t - \mathbf{L}_{t-T} = \mathbf{X}\left(\boldsymbol{\beta}_t - \boldsymbol{\beta}_{t-T}\right) + \underbrace{\left(\boldsymbol{\upsilon}_t - \boldsymbol{\upsilon}_{t-T}\right) + \left(\left(\mathbf{L}_t - \mathbf{L}_t^*\right) - \left(\mathbf{L}_{t-T} - \mathbf{L}_{t-T}^*\right)\right)}_{\text{disturbance term}} \tag{3a}$$

As with (2a), the latter elements of the disturbance term are likely to be correlated with $\mathbf{X}$, yielding biased estimates of $\boldsymbol{\beta}_t - \boldsymbol{\beta}_{t-T}$. To illustrate, once again assume deterministic linear convergence and a once-and-for-all shift from $\boldsymbol{\beta}_{t-\tau}$ to $\boldsymbol{\beta}_t$. Then (2b) can be differenced to give

$$\mathbf{L}_t - \mathbf{L}_{t-T} = \begin{cases} \left(e^{-\lambda(\tau-T)} - e^{-\lambda(\tau)}\right)\left(\mathbf{X}\left(\boldsymbol{\beta}_t - \boldsymbol{\beta}_{t-\tau}\right) + \left(\boldsymbol{\upsilon}_t - \boldsymbol{\upsilon}_{t-\tau}\right)\right) & : \quad t-\tau < t-T < t \\ \left(1 - e^{-\lambda(\tau)}\right)\left(\mathbf{X}\left(\boldsymbol{\beta}_t - \boldsymbol{\beta}_{t-\tau}\right) + \left(\boldsymbol{\upsilon}_t - \boldsymbol{\upsilon}_{t-\tau}\right)\right) & : \quad t-T < t-\tau < t \end{cases} \tag{3b}$$

So with strong assumptions, a regression based on (3a) would produce expected coefficients equal to a positive scalar times the change in underlying structural parameters, $\mathrm{E}\left(\mathbf{b}_t - \mathbf{b}_{t-\tau}\right) = \alpha\left(\boldsymbol{\beta}_t - \boldsymbol{\beta}_{t-\tau}\right)$ with $0 < \alpha(\lambda, \tau, T, t) < 1$.

A large body of research suggests that local productivity and quality of life exhibit some increasing returns to scale with respect to population (e.g., Henderson et al, 1995; Ades and Glaeser, 1999; Costa and Kahn, 2000; Henderson, 2003). If so, steady-state population density will be subject to path dependence. This suggests an alternative linear data-generating process,

$$\mathbf{L}_t^* = \gamma \mathbf{L}_{t-T} + \mathbf{X}\boldsymbol{\delta}_t + \boldsymbol{\upsilon}_t \qquad 0 < \gamma < 1 \tag{4}$$

The parameter $\boldsymbol{\delta}_t$ measures the *partial* effect of $\mathbf{x}_i$ on $\mathbf{L}_i^*$ controlling for $\mathbf{L}_{t-T}$, which itself is likely to be a function of $\mathbf{x}_i$. Thus rather than as a measure of a structural relationship, $\boldsymbol{\delta}_t$ is better interpreted as capturing the change in effect of $\mathbf{x}_i$ on steady-state economic density. To emphasize this change interpretation, it is helpful to subtract lagged population density from both sides. Doing so, and taking account of the unobservability of steady-state density, the data-generating process to be estimated becomes

$$\mathbf{L}_t - \mathbf{L}_{t-T} = -\left(1-\gamma\right)\mathbf{L}_{t-T} + \mathbf{X}\boldsymbol{\delta}_t + \underbrace{\boldsymbol{\upsilon}_t + \left(\mathbf{L}_t - \mathbf{L}_t^*\right)}_{\text{disturbance term}} \tag{5a}$$

The difference between steady-state and current population density again gets subsumed in the disturbance term. With deterministic linear convergence, (5a) can then be rewritten as

$$\mathbf{L}_t - \mathbf{L}_{t-T} = -(1-\gamma)\left(1-e^{-\lambda T}\right)\mathbf{L}_{t-T} \; + \; \left(1-e^{-\lambda T}\right)\mathbf{X}\boldsymbol{\delta}_t \; + \; \left(1-e^{-\lambda T}\right)\boldsymbol{\upsilon}_t \tag{5b}$$

The coefficients on $\mathbf{X}$ from regressions based on (5b) will thus give unbiased estimates of the sign of the components of $\boldsymbol{\delta}_t$.

Note that (3a) and (3b) versus (5a) and (5b) differ only by the latter pair's inclusion of lagged population density as a right-hand-side variable.[5]

Regressions using county observations almost surely violate the classical assumption of independence. Hence I use a generalization of the Huber-White heteroskedastic-consistent estimator based on Conley (1999) to report standard errors robust to a spatial structure among disturbance terms. For observation pairs between which the Euclidean distance is beyond a certain cutoff. I impose that the covariance between disturbances is zero. Within this distance, I impose a declining weighting function for estimating the covariance between disturbances. In essence, this amounts to allowing for a spatially-based random effect. Letting $\mathrm{s}_{i,j}$ be the estimate of $\sigma_{i,j}$ and u_i be a regression residual,

$$E\left(\upsilon_i \upsilon_j\right) = \begin{cases} \sigma_{i,j} & : \quad \text{distance}_{i,j} \leq \overline{d} \\ 0 & : \quad \text{distance}_{i,j} > \overline{d} \end{cases} \tag{6}$$

$$\mathrm{s}_{i,j} = g\left(\text{distance}_{i,j}\right)\mathrm{u}_i\mathrm{u}_j \tag{7}$$

[5]If (4) is the true data-generating process, the actual disturbance in (3b) should include the term $-(1-\gamma)\left(1-e^{-\lambda T}\right)\mathbf{L}_{t-T}$. But the bias from using (3b) to estimate $\boldsymbol{\delta}_t$ (i.e., from incorrectly excluding lagged population density on the RHS) need not be large, especially for $\gamma \approx 1$ or λT small. On the other hand, if (1) is the true data-generating process, the inclusion of initial density on the RHS of (3b) implies the coefficients on $\mathbf{X}$ will measure a positive scalar times $\boldsymbol{\beta}_t$ rather than $\left(\boldsymbol{\beta}_t - \boldsymbol{\beta}_{t-T}\right)$ In practice, the inclusion of lagged population density causes almost no change relative to (3b) in the estimated coefficients on the remaining RHS variables. This suggests that (4) is the more likely data-generating process and that the coefficients on $\mathbf{X}$ should indeed be interpreted as describing the change in an underlying structural relationship rather than the structural relationship itself.

$$
\begin{aligned}
g\left(\text{distance}_{i,j}\right) & \begin{cases} = 1 & : \quad \text{distance}_{i,j} = 0 \\ \in [0,1] & : \quad 0 < \text{distance}_{i,j} \leq \overline{d} \\ = 0 & : \quad \text{distance}_{i,j} > \overline{d} \end{cases} \\
g'\left(\text{distance}_{i,j}\right) & \leq 0
\end{aligned} \qquad (8)
$$

Herein, I assume the weighting in the estimated covariance between residual terms falls off quadratically as the distance between county centers increases to 200 kilometers, the cutoff beyond which I impose zero covariance. Thus accounting for spatial correlation approximately doubles standard errors relative to the assumption of zero covariance with homoskedastic disturbances.[6]

4 Data Description

U.S. counties are used as the geographic unit of analysis. Doing so offers several benefits relative to using alternative U.S. local geographies. First, counties completely partition the continental United States; excluding geographic areas with low population would introduce a source of considerable bias. Second, counties' borders have been relatively constant across time. Constant borders allow intertemporal comparisons between geographically fixed areas and can be considered exogenous relative to most data-generating processes.[7] Third, coun-

[6]So $g(\cdot) = 1 - \left(\frac{\text{distance}_{i,j}}{200}\right)^2$. Note that the specification in (7) and (8) reduces to the Huber-White heteroskedastic-consistent estimator for standard errors when $\overline{d}$ equals zero; it reduces to a group-based random effect estimator for standard errors with a non-Euclidean one-zero step specification for $g(\cdot)$.

[7]I do make a few adjustments to county geographies. First is to include the District of Columbia as a county equivalent. Second is to combine "independent cities" with the counties that completely surround them but from which they are formally separate (especially common in Virginia). Third is to adjust for the occasional county border change. Most frequently such changes take the form of the splitting of a county into two or more counties. Wherever possible, I have recombined such "split" counties to allow for intertemporal comparisons, based primarily on Horan and Hargis (1995) and Thorndale and Dollarhide (1987). I limit such adjustments to only those regressions for which it is required. So, for instance, no such adjustments are needed when 2000 population density is the dependent variable; and only a handful are needed when population growth from 1960 to 2000 is the dependent variable. But more adjustments are needed for the growth regressions from earlier in the twentieth century. When such adjustments are needed, weather, coast,

ties' small size implies that the weather tends to be relatively uniform throughout them. Fourth, the large number of U.S. counties (3,069 in 2000) and the wide variation in weather across them allows for a rich description of the partial correlations with population density.

The regression results below focus on two main dependent variables: the *level* of population density in 2000 and the *growth rate* of population density from 1960 to 2000. Underlying population and land area for 2000 are from the 2000 decennial census, Summary Files 1 and 3. Underlying population and land area for 1960 are from the 1947-to-1977 consolidated City and County Data Book data file. Underlying population and land area data for the remaining decade-by-decade population density growth regressions are from corresponding decennial census data as disseminated in electronic form by several sources listed in the bibliography. A few regressions focus on the level and growth rate of employment density. Underlying employment data are from the U.S. Department of Commerce's Bureau for Economic Analysis *Regional Economic Information System*.

The weather variables are derived from data purchased from www.climatesource.com. The Climate Source data, in turn, is based on detailed weather observations over the period 1961 to 1990 from more than 6,000 meteorological stations managed by the U.S. National Oceanographic and Atmospheric Administration. A peer-reviewed "hybrid statistical-geographical methodology" developed by researchers at the Spatial Climate Analysis Service at Oregon State University is applied to such data to fit surfaces over a 2 km grid of the continental United States. The methodology includes considerable attention to accurately measuring highly-varying weather near coasts and mountains. A county's weather values are then constructed as the mean over all 4 km^2 grid cells that lie within it.

Results are presented for six winter, seven summer, and seven precipitation elements. Table 2 shows summary statistics; Supplemental Table 3 shows correlations among the elements.[8]

The winter weather variables measure how cold a place gets. "January daily minimum

and topography variables are calculated as a land weighted average of present-day constituent values.

[8]Supplemental color maps showing the distribution of several of these weather elements across the continental U.S. are available from www.kc.frb.org/Econres/staff/jmr.htm

temperature" is the average minimum temperature for days in January; in other words, it is the mean of the coldest temperature attained on each of the 930 January days from 1961 to 1990. "January daily maximum temperature" is the average maximum temperature for days in January. "January daily mean temperature" is the mean of January daily minimum temperature and January daily maximum temperature. "Annual extreme minimum temperature" is the average of the lowest minimum temperature for each of the thirty years. "Annual low temperature days" is the average number of days per year that the minimum temperature falls to 32°F or less. "Annual heating degree days" is the average number of heating degree days per year; each heating degree day represents a 1°F increment below 65°F in a day's mean temperature.

The summer weather variables measure how hot a place gets. They are defined analogously to their winter counterparts. "Annual high temperature days" is the average number of days per year that the maximum temperature rises to 90°F or more. Each cooling degree day represents a 1°F increment above 65°F in a day's mean temperature. "July daily heat index" is a discomfort index combining July daily maximum temperature and July daily relative humidity (Stull, 2000).

The precipitation variables are mostly self-explanatory. "Annual snow days" is the average number of days per year on which there is at least 0.1 inches of snow. "Annual precipitation days" is the average number of days per year on which there is at least 0.01 inches of precipitation. Precipitation days may also proxy for sunshine, measures of which are often used to describe the weather of metropolitan areas and large municipalities. For counties, a more direct measure of sunshine is not available since only about 300 weather stations collect data on sunshine. "July daily relative humidity" is calculated using July daily mean temperature and July daily mean dew point.

Some of the regressions include a set of seven geographic controls measuring coastal proximity and topography. Separate dummies indicate whether a county's center is within 80 kilometers of an ocean or Great Lakes coast or within 40 kilometers of a major river. Additional variables measure log(1 + ocean shoreline per unit area) and log(1 + Great Lakes shoreline per unit area) (2 variables). And a topography variable, entered linearly and quadratically, measures the standard deviation of altitude across 1.25 arc minute grid cells within a county divided by total county land area.

Some of the growth regressions include an additional set of fourteen variables measuring initial population density and surrounding total population. The inclusion of these variables is premised on the path dependence of steady-state population density as in (4). Initial population density is entered as a seven-part spline to allow for a nonlinear relationship between initial and steady-state population density. Surrounding total population is the initial total population in seven concentric rings emanating from a county's center. An innermost circle measures log(1 + total population of all counties with centers within 50 km from a county's own center) and, at a minimum, always includes the county's own population. A second ring measures log(1 + total population of all counties with centers 50 to 100 km from a county's own center); additional rings with outer circumference radii of 150 kilometers, 200 kilometers, 300 kilometers, 400 kilometers, and 500 kilometers make for a total of 7 rings. Together, these concentric population variables capture, for instance, the "market potential" available to local firms producing goods with nontrivial transportation costs (Krugman, 1991; Ades and Glaeser, 1999; Fujita, Krugman, Venables, 1999; Hanson, 2001; Black and Henderson, 2002).

5 Level Results

This section describes partial correlations between population density in 2000 and a few combinations of the winter, summer, and precipitation variables. More specifically, Tables 3, 4, and 5 report results from regressing log(1 + Population Density) on a constant, the listed weather elements, and the square of the listed elements minus their sample mean. Adding one to the dependent variable implicitly down-weights extremely sparsely settled counties, where idiosyncratic factors presumably account for a larger portion of variation. Removing sample means in the construction of quadratic independent variables allows coefficients on the corresponding linear independent variables to measure partial correlations at these sample means. Map 1 shows the exponentiated dependent variable normalized by U.S. population density.

Table 3 reports partial correlations between population density and each of the weather elements individually. There are four main results. First, population is concentrated in counties with moderate winters. The negative, statistically significant quadratic coefficients imply that a maximum density is associated with an intermediate level of each of the six winter variables. The linear coefficients imply that density is positively correlated with warmer winters at the means of each of the variables. For instance, density is positively correlated with January daily mean temperature at its 31°F sample mean. The positive correlation falls off as temperature increases until density is "maximized" at 46°F. Above this, density is increasingly negatively correlated with January daily mean temperature.

Second, population is concentrated in counties with moderate summers. Negative, statistically significant quadratic coefficients apply to five of the seven summer variables and a sixth negative quadratic coefficient statistically differs from zero at the 0.10 level. The linear summer coefficients imply that maximum density is associated with summer temperatures slightly above the sample mean for some of the variables and slightly below it for others.

Third, population is concentrated in counties with relatively high rain and humidity but low snow. Negative, statistically significant quadratic coefficients apply to both annual precipitation and annual precipitation days. The implied annual precipitation and precipitation days associated with maximum density are 58 inches and 145 days, which are respectively 1.4 and 2.1 standard deviations above their sample means. A positive, statistically significant quadratic coefficient applies to July humidity; along with the corresponding linear coefficient, it implies that minimum density is associated with 34 percent relative humidity. Since this is near the very lowest of observed humidity values, in general density is positively correlated with higher humidity. Density is negatively correlated with annual snowfall as well as with 5-inch and 10-inch snow days.

Fourth, some weather elements account for much more of the variation in population density than others. Annual precipitation, annual precipitation days, and July relative humidity account for by far the highest variation, with each having $R^2 \geq 0.21$. Among the winter elements, cold temperature days accounts for the largest variation, with $R^2 = 0.134$.

Among the summer elements, annual extreme maximum temperature accounts for the largest variation, with $R^2 = 0.112$.

Table 4 reports results from regressions of population density on paired winter and summer variables. Controlling for summer weather, population density is unambiguously positively correlated with warmer winters. This positive correlation holds across the entire range of observed values of all the winter variables except extreme minimum temperature. Unsurprisingly, the magnitude of the positive correlation at the variables' sample means is larger than the corresponding magnitude when not controlling for summer weather. The negative quadratic coefficients imply that the positive correlation weakens as winters become warmer.

Even after controlling for winter weather, population density continues to be concentrated in counties with moderate summers. At the variables' sample means, density is negatively correlated with warmer summer weather. The magnitude of this negative correlation is larger compared to the corresponding magnitude when not controlling for winter weather. The quadratic coefficients for all summer variables except hot temperature days and cooling degree days imply that the summer temperatures associated with maximum density lie approximately one standard deviation below sample means. For hot temperature days and cooling degree days, the negative correlation with warmer weather holds across the entire range of observed values.

Among the various paired winter and summer variables, the combination of cold temperature days and hot temperature days accounts for by far the largest variation in population density, with $R^2 = 0.419$.

Finally, Table 5 reports results from regressions of population density and employment density on the cold and hot temperature days combination along with annual precipitation. Columns 2 and 4 also include the set of 7 coast and topography controls enumerated in the data description section. Columns 3 and 6 additionally include dummies for the nine Census geographic divisions. These multiple-weather-element level regressions admit very similar coefficients, regardless of whether population density or employment density is the dependent variable and regardless of whether the coast and topography and the census division controls are included. Similar results are also obtained from including dummies for each of the forty-eight continental U.S. states (not shown).

As above, density continues to show strong, statistically significant negative partial correlations with the annual number of cold and hot temperature days. Both negative correlations hold across the entire range of observed values. For the Column 2 regression, increasing the number of cold temperature days by one standard deviation (52 days) from its mean (113 days) is associated with a 73 percent decrease in expected population density. Increasing the number of hot temperature days one standard deviation (32 days) from its mean (42 days) is associated with a 62 percent decrease in expected population density.

Controlling for cold and hot temperature days, population density is concentrated in counties with moderate annual precipitation. Maximum population and employment density are associated with annual precipitation in the range of 30 to 37 inches per year. For the Column 2 regression, increasing annual precipitation by one standard deviation (14 inches) from its sample mean (38 inches) is associated with a 22 percent fall in population density.

The three weather elements in Table 5 account for an extremely high share of the variation of density across counties. For population density, $R^2 = 0.464$; for employment density, $R^2 = 0.385$. For comparison, regressing county population and employment density on a constant and 48 state dummies respectively gives $R^2 = 0.408$ and $R^2 = 0.343$.

Map 2 shows counties' expected population density attributable to weather. The map is constructed based on an expanded version of the regression shown in Table 5, Column 2.[9] Expected density captures the combined past and present contributions to local productivity and quality of life from the weather along with the combined past and present contributions to these from any local characteristics correlated with the weather but excluded from the underlying regression. Regions with weather suggesting the highest expected population

[9] The expanded regression, shown in Supplemental Table 4, continues to control for coastal proximity and topography but increases the number of weather elements from three to nine. Doing so increases the accounted share of variation from $R^2 = 0.500$ to $R^2 = 0.551$. Expected population density is constructed by applying the coefficients on the weather elements to counties' actual weather characteristics. The resulting vector product is then transformed to show (1 + fitted county population density)/(1 + U.S. population density).

density include the Atlantic coast from Connecticut south to North Carolina; northwest New York state from Rochester west to Buffalo; northern Ohio, northern Indiana, and southern Michigan; and a few scattered Gulf coast and Pacific coast counties.

6 Growth Results

Technological innovation and rising incomes suggest that the productivity and quality-of-life contributions from weather are likely to have changed considerably over the course of the twentieth century. Growth regressions of the form (3a) and (5a) can identify the direction of such changes. Regressing the 1960-to-2000 growth of population density on the various weather elements shows growth to be strongly positively correlated with warm winters and strongly negatively correlated with hot and humid summers. Comparing actual partial correlations against those predicted by the introduction and spread of air conditioning and improved heating technologies suggests that a large portion of the migration towards mild weather is motivated by quality-of-life considerations.

Table 6 reports results from regressing $[(\log(1 + 2000 \text{ Population Density}) - \log(1 + 1960 \text{ Population Density})) \times 100/40]$ on a constant, each of the listed weather variables, and the square of each of the listed weather variables minus its sample mean. Map 3 shows the dependent variable. As discussed in the specification section, the interpretation of coefficients is that they measure the sign of changes in structural relationships. Because of the slow adjustment of population to its steady state, this change is inferred to have occurred at some time prior to 2000 (but either before or after 1960).

The univariate correlations establish that warm winters are the most important weather characteristic driving counties' growth. This is unsurprising given the widely recognized shift of U.S. population to "sun belt" locations such as California, Arizona, and Florida. The linear coefficients show that growth is positively correlated with warmer winters at the means of each of the six winter variables. The positive quadratic coefficients imply weather values associated with minimum growth rates. However, except for cold temperature days and heating degree days, the implied "worst" weather values are very close to minimum observed weather values. So the positive quadratic coefficients are best interpreted as implying that the positive correlation between growth and winter temperature becomes stronger the warmer the winter. In other words, there is a larger increase in growth associated with January temperature rising from 55°F to 65°F than from its rising from 45°F to 55°F. The winter variables have much higher explanatory power than either the summer weather variables or the rain, snow, and humidity variables. Among the winter variables, January daily minimum temperature accounts for the largest share of variation in growth rates, with $R^2 = 0.125$.

The univariate correlations between growth and summer weather are much weaker. Except for extreme maximum temperature, the linear coefficients show that growth is positively correlated with hotter summers at variable sample means. The positive quadratic coefficients imply that growth is negatively correlated with warmer summers at temperatures somewhat below variable sample means. Except for annual cooling degree days, explanatory power is quite low, with $R^2 \leq 0.021$.

The negative partial correlation between growth and hot summers becomes evident from growth regressions that include both winter and summer elements. Table 7 shows results from regressing growth on paired winter and summer variables. For each of the seven pairs, the coefficient on the linear winter variable is positive and the coefficient on the linear summer variable is negative. So at mean levels of the variables, growth is positively correlated with warmer winters and negatively correlated with hotter summers. For the most part, the quadratic coefficients on both the winter and summer variables imply best or worst weather outside or nearly outside the range of observed values. The positive quadratic winter coefficients imply that the positive correlation between growth and warmer winter weather becomes stronger the warmer the winter. And the negative quadratic summer coefficients imply that the negative correlation between growth and hotter summer weather becomes more negative the hotter the summer. The combination accounting for the highest percentage of the variation in growth rates is January minimum temperature paired with July heat index, with $R^2 = 0.216$. The finding of a negative partial correlation between growth and summer temperature contrasts with Glaeser and Shapiro (2003), who find these to be positively correlated both for U.S. metropolitan areas and for large U.S. municipalities.

Table 8 reports results from regressing population growth on a relatively sparse specification of five weather elements. The Column 2 regression additionally includes variables measuring coastal and river proximity and topography. The Column 3 regression also controls for initial density using a five-part spline and for total population in each of five concentric rings emanating from a county's center. The Column 4 regression adds fixed effects for the Census Bureau's nine geographic divisions. The Column 5 regression substitutes state fixed effects for the Census division fixed effects. The specific five elements — January maximum temperature, July heat index, July relative humidity, annual precipitation, and annual precipitation days — were chosen to minimize the sum of squared residuals for a growth regression that controls for coastal proximity, topography, initial density, and concentric total population while sparsely representing the three categories of weather variables. Unless otherwise noted, qualitative results are extremely robust to alternative choices of the specific weather elements.

The multiple element regressions affirm that 1960-to-2000 population growth is strongly positively correlated with warm winter weather and strongly negatively correlated with hot and humid summer weather. All five regressions admit statistically significant, quantitatively large positive coefficients on both linear and quadratic January maximum temperature. Similarly, all five regressions admit statistically significant, quantitatively large negative coefficients on both linear July heat index and linear July relative humidity. In addition, a negative coefficient on quadratic July heat index is statistically significant in the Column 1 and 2 regressions; and a negative coefficient on quadratic July relative humidity is statistically significant in the Column 3, 4, and 5 regressions. Using the Column 3 regression as a benchmark, a one standard deviation increase in January daily maximum temperature from its mean is associated with faster annual growth of 0.86 percentage points.[10] A one standard deviation increase in July daily heat index from its mean, holding July daily relative hu-

[10] The Column 3 regression is used as a benchmark given the overwhelming empirical evidence that initial population density and surrounding total population are strongly correlated with growth. Excluding either the five initial density variables or the five surrounding total population variables from the Column 3 regression causes R^2 to drop by more than six percentage points, so that an F-test easily rejects that the variables are not statistically significant.

midity constant (i.e., the increase in heat index comes solely from an increase in July daily maximum temperature), is associated with slower annual growth of 0.44 percentage points. A one standard deviation increase in July relative humidity from its mean, allowing for the implied increase in July daily heat index, is associated with slower annual growth of 0.75 percentage points.

The Table 8 regressions also show statistically significant but quantitatively small partial correlations of growth with precipitation. Growth is positively correlated with annual rainfall and positively correlated with annual rainy days when there are few rainy days but negatively correlated with annual rainy days when there are many rainy days. Four of the five regressions admit a statistically significant positive coefficient on linear annual precipitation, though this is fragile to the exclusion of July relative humidity. The statistically significant, negative quadratic coefficients on annual precipitation in the Column 1 and 2 regressions imply that growth is maximized at annual precipitation approximately two standard deviations above the sample mean. Based on the benchmark Column 3 regression, increasing annual precipitation from its mean (38.2") by one standard deviation (14.1") is associated with faster annual growth of 0.21 percentage points. All five regressions admit a statistically insignificant positive coefficient on linear precipitation days and a statistically significant negative coefficient on quadratic precipitation days. Together, these imply growth is maximized at approximately one half a standard deviation above the precipitation days sample mean (94 days). For the Column 3 regression, increasing precipitation days from its "best" level (101 days) by one standard deviation (25 days) is associated with slower growth of 0.10 percentage points.

Weather, coastal proximity, initial population density, and surrounding total population together account for a relatively large share of the variation in county growth rates. With just the five weather elements, R^2 equals 0.239. Additionally controlling for coastal and river proximity and topography, R^2 equals 0.263. Additionally controlling for initial population density and surrounding total population, R^2 equals 0.385. For comparison, regressing county population density growth on a constant and 48 state dummies gives an R^2 of 0.274.

Comparing hypothesized to actual correlations, the results strongly reject that observed weather-related moves are motivated solely by the introduction of air conditioning. In particular, the partial correlation of growth with summer temperature is negative rather than positive (Table 1). Similarly, the results reject that weather-related moves are motivated by improved heating technologies. A particular, the partial correlation of growth with winter temperature is positive rather than negative. In contrast, both of these actual partial correlations are exactly what would be expected if weather-related moves reflected individuals' increasing demand for nice weather as a quality-of-life amenity.

The timing of the population shift towards nice weather locations reinforces that it has been driven by more than air conditioning. Table 9 reports decade-by-decade regressions analogous to those of Table 8 Column 3. These show statistically significant positive partial correlations of growth with warmer winters and statistically significant negative partial correlations of growth with hotter summers for every decade starting with the 1920s. As the mass adoption of air conditioning did not start until after World War II, air conditioning would seem an unlikely explanation for these trends. The same regressions show statistically significant negative partial correlations of growth with July humidity for every decade starting with the 1950s, exactly when the spread of air conditioning was making humid summers less unpleasant. Consistent with an increasing income-driven movement towards higher quality of life, the positive partial correlation between growth and warmer winters was much smaller during the Great Depression 1930s than during either the 1920s or the 1940s and 1950s. The share of the variation of growth accounted for by the weather was also much less during the 1930s than during the 1920s or the 1940s and 1950s.[11]

An obvious question is to what extent does the move towards high quality-of-life weather reflect an increasingly mobile and financially secure elderly population. Empirical evidence suggests very little. Table 10 shows results from regressions identical to those in Table 8 except that the growth of population density is calculated using just working-age individuals (aged 21 to 64) for the Column 1 to 3 regressions and using just seniors (aged 65 and above) for the Column 4 to 6 regressions. The working age population growth regressions admit coefficients nearly identical in magnitude and statistical significance to the analogous

[11]Identical results are obtained if dummies for the nine Census Bureau geographic divisions or the forty-eight continental U.S. states are included.

total population growth regressions. Similarly, regressions using employment growth as the dependent variable admit coefficients with nearly the same magnitude and statistical significance as population growth regressions (Supplemental Table 5).

Another possibility is that elderly migration served as a catalyst for younger migration and employment growth. But the magnitudes of the partial correlations between growth and nice weather are actually slightly larger for the working-age population than for the elderly. Moreover, the movement towards nice weather dates back to the 1920s, when presumably the elderly were much less mobile. On the other hand, the weather elements do account for a substantially higher percentage of the variation in seniors' population growth than they do for working-age population growth.

Map 4 shows counties' expected 1960-to-2000 population density growth attributable to weather. The map is constructed based on an expanded version of the benchmark regression shown in Table 8 Column 3.[12] Expected growth captures the *change* in the weather's contribution to productivity and quality of life along with the change in the contribution to these from any characteristics correlated with the weather but excluded from the underlying regression. Regions with weather suggesting the highest expected population growth include the Florida peninsula; the desert areas of western Arizona, southern California, and southern Nevada; the Sierra Nevada and Cascade ranges from central California north through southern Oregon; and some scattered counties in the mountain west states of Colorado, Wyoming, Montana, and Idaho.

[12] The expanded regression, shown in Supplemental Table 6, continues to control for coastal proximity and topography, initial population density, and concentric total population. It increases the number of weather elements from 5 to 11. Doing so increases explanatory power from $R^2 = 0.385$ to $R^2 = 0.429$. For each of the 11 elements, either the coefficient on the linear variable or the coefficient on the quadratic variable (or both) statistically differs from zero at the 0.05 level. Expected population growth is calculated by applying the coefficients on the weather elements to counties' actual weather characteristics.

7 What Do We Learn from Growth Regressions?

A strong criticism of cross-country per capita income growth regressions is that they measure good luck rather than good fundamentals (Easterly et al., 1993). In particular, countries' per capita income growth shows very little persistence across decades, in contrast to the highly persistent right-hand-side variables commonly included in such regressions. Such a criticism does not apply to the present cross-county growth regressions since county population growth rates are highly persistent across time (Rappaport 2002). Moreover, a ranking of localities based on their fitted growth attributable to weather is highly correlated with an a priori quality-of-life ranking of these localities' weather. This high correlation also bolsters the conclusion that quality of life is becoming a much more important consideration affecting locational decisions.

The a priori ranking is based on an index of weather's contribution to quality of life for 354 U.S. and Canadian metropolitan areas published in the *Places Rated Almanac* (Savageau and D'Agostino, 2000).[13] The fitted growth ranking is constructed by applying the coefficients on the weather variables from the regression underlying Map 4 (i.e., the regression using county observations reported in Supplemental Table 6) to the actual weather characteristics for 304 U.S. urbanized areas that I am able to match to the *Places Rated* metropolitan areas.[14]

[13] The *Places Rated* ranking is constructed by averaging index scores from four subsets of weather attributes: winter mildness, summer mildness, "hazardousness", and "seasonal affect". Winter mildness is constructed as a mean index of cold temperature days, mean daily temperature for the coldest month, and a measure of winter windchill. Summer mildness is constructed as the mean of hot temperature days, mean daily temperature for the hottest month, and annual relative humidity. Hazardousness is constructed as the weighted mean of annual snowfall, the frequency of thunderstorms, and the frequency of strong winds with respective relative weights of 9:3:1. Seasonal affect is constructed as the weighted mean of annual cloudy days (more than 80 perecent cloud cover), annual days with precipitation greater than 0.1 inch, annual fog days (visibility less than one-half mile), and latitude (to indicate potential sunlight) with respective relative weights 4:4:2:1. The underlying weather data is measured by a single weather station which is assumed to be representative for a metropolitan area.

[14] Urbanized areas are densely settled territory containing 50,000 or more people and tend to be considerably smaller than metropolitan statistical areas. As with the county weather data, the urbanized area

Fitted level rankings are similarly constructed using the coefficients from the regression underlying Map 2 (i.e., the regression using county observations reported in Supplemental Table 4). Supplemental Table 7 shows the *Places Rated* ranking, the fitted growth ranking, and the fitted level ranking for one hundred of the 304 matched cities along with a few key weather elements used to construct the fitted rankings.

Comparing rankings amounts to comparing preference orderings of different weather bundles. The fitted growth ranking and the *Places Rated* ranking are highly correlated. The Spearman correlation coefficient between the two is 0.74. This high correlation is extremely robust to alternative growth regression specifications. In sharp contrast, the fitted level ranking is approximately orthogonal to the *Places Rated* ranking. The Spearman correlation coefficient between the two is -0.11, though it does not statistically differ from zero at the 0.05 level. This approximate orthogonality is extremely robust to alternative level regression specifications.

Since present contributions to welfare are the sum of past contributions to welfare plus changes in contributions to welfare, it is intuitive that a convex additive combination of fitted population density and fitted population growth should do a better job matching *steady-state* population density attributable to weather than either of these alone. Combining the fitted level and growth values based on the regressions underlying Maps 2 and 4, the Spearman correlation with the *Places Rated* ranking rises from 0.74 with 100 percent of the weight put on the growth regression to 0.78 with 86 percent of the weight put on the growth regression. Combining the fitted level and growth values based on the more sparse regressions shown in Table 5 Column 2 and Table 8 Column 3, the Spearman correlation coefficient rises from 0.76 with 100 percent of the weight put on the growth regression to 0.80 with 84 percent of the weight put on the growth regression.

There are several reasons for thinking that fitted growth's correlation with the *Places Rated* quality-of-life index overstates fitted growth's correlation with welfare. The most obvious is that weather's contribution to welfare includes not just its contribution to quality of life but also its contribution to productivity. Second, many of the high-fitted-growth coun-

weather data is based on a geographic average of values for 4 km^2 grid cells.

ties shown in Map 4 suffer from severe water shortages and experience frequent forest fires, reflecting low annual precipitation. Third, the *Places Rated* ranking arguably underweights the discomfort associated with hot, humid weather. For instance, seventeen of its top thirty ranked cities (among the 304 matched observations) have an average July daily heat index of 104° or higher; eight have an average July daily heat index of 110° or higher. These same reasons also suggest that fitted population density's correlation with the *Places Rated* ranking may understate its correlation with welfare.

Such caveats notwithstanding, fitted growth's high correlation with an a priori quality-of-life ranking is nevertheless surprising. After all, the fitted growth ranking should measure the *change* in an underlying steady-state relationship rather than the *level* of a current steady-state relationship. But the high correlation does make sense for a current steady-state relationship that is orthogonal to current density, exactly as suggested by the near-zero correlation of the fitted level ranking with the a priori quality-of-life ranking. In this special case, the change in the underlying steady-state relationship will itself be highly correlated with the current level of that steady-state relationship.[15] But more generally, growth regressions may poorly describe steady-state relationships.

On the other hand, the high correlation between the fitted growth ranking and the a priori quality-of-life ranking does suggest that weather's quality-of-life contribution to welfare rather than its productivity contribution to welfare has been the main source of the partial correlations between population growth and the various weather elements. This bolsters the conclusion that quality of life is becoming an increasingly important determinant of locational decisions. Furthermore, the low correlation of the fitted level ranking and the a priori quality-of-life ranking suggests that a large distance remains between the current geographic distribution of population and a steady-state distribution that reflects weather's current contribution to quality of life. So weather's contribution to quality of life is likely to continue to shape growth well into the future.

[15] For instance, consider a deterministic framework in which $\mathbf{L}^*_{t-\tau} = \mathbf{X}\beta_{t-\tau}$ and $\mathbf{L}^*_t = \mathbf{X}\beta_t$. If the n-by-1 past and present steady-state population density vectors are orthogonal but of equal magnitude, $(\mathbf{X}\beta_{t-\tau})'(\mathbf{X}\beta_t) = 0$ and $\left|\mathbf{X}\beta_{t-\tau}\right| = |\mathbf{X}\beta_t|$, the resulting 45° angle between $\left(\mathbf{L}^*_t - \mathbf{L}^*_{t-\tau}\right)$ and $\mathbf{L}^*_t$ implies a correlation between the two of $\rho = 0.71$.

8 Conclusions

Local population growth in the United States has been highly correlated with warmer winter weather and cooler, less humid summer weather. While the introduction and spread of air conditioning may have been a prerequisite for the former trend, the latter trend suggests that air conditioning has not been the main driving force. Nor can elderly migration account for this growth pattern. Instead, the empirical results suggest that the movement towards nice weather has been driven by people's increasing their valuation of the weather's contribution to their quality of life.

An increasing valuation of quality of life is consistent with the broad-based rise in U.S. per capita income over the twentieth century. Hence it seems likely that U.S. residents have also increased their valuation of other local attributes that increase quality of life. Some local attributes that possibly do so include scenic amenities, recreational amenities, low pollution, and high quality schools.

Fitted results from population growth regressions do an excellent job matching an a priori ranking of the weather's contribution to quality of life. This reinforces the conclusion that variations in local quality of life underlie a large portion of variations in local growth. More generally, population growth regressions are expected to describe changes in the contributions to welfare from local attributes.

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Table 1: Expected and Actual Correlations

	Correlation with Winter Temperature		Correlation with Summer Temperature	
	raw	partial	raw	partial
(1) Expected Pop Density		+		-
(2) Actual Pop Density	+	+	-	-
<u>Expected Growth due to:</u>				
(3) Air-Conditioning	+	+	+	+
(4) Improved Heating	-	-	-	-
(5) Increased Valuation of Quality of Life		+		-
(6) Actual Growth	+	+	+	-

Table 2: Summary Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Land Area/Population/Employment:					
2000 Land Area (sq.km)	3,069	2,497	3,390	59	51,936
2000 Population	3,069	91,099	296,317	67	9,519,338
2000 Population Density (per sq.km)	3,069	86.0	642.8	0.0	25,845.7
log(1+2000 Population Density)	3,069	2.93	1.43	0.04	10.16
1960-to-2000 Change in log(1+Pop Density)*	3,063	0.72	1.14	-2.33	8.10
1960-to-2000 Change in log(1+WrkAge Density)*	3,063	0.99	1.14	-1.81	7.99
1960-to-2000 Change in log(1+Seniors Density)*	3,063	1.01	0.97	-1.68	6.75
2000 Employment	3,069	53,519	188,142	123	5,492,154
2000 Employment Density (per sq.km)	3,069	59.8	883.1	0.05	47,271
log(1+2000 Employment Density)	3,063	2.34	1.39	0.05	10.76
Winter Weather					
January Daily Mean Temperature (°F)	3,069	30.8	11.8	0.2	65.9
January Daily Minimum Temperature (°F)	3,069	20.2	11.4	-10.8	55.4
January Daily MaximumTemperature (°F)	3,069	41.4	12.4	10.8	76.5
Annual Extreme Minimum Temperature (°F)	3,069	-4.0	14.5	-37.6	34.9
Annual Cold Temperature Days	3,069	112.7	51.9	0	270.7
Annual Heating Degree Days	3,069	5,147	2,262	232	12,025
Summer Weather					
July Daily Mean Temperature (°F)	3,069	75.2	5.6	52.2	92.3
July Daily Minimum Temperature (°F)	3,069	63.1	6.6	36.9	78.4
July Daily Maximum Temperature (°F)	3,069	87.4	5.1	66.8	106.1
Annual Extreme Maximum Temperature (°F)	3,069	97.7	4.3	75.8	115.4
Annual Hot Temperature Days	3,069	42.4	31.6	0	169.5
Annual Cooling Degree Days	3,069	1,188	763	1	3,917
July Daily Heat Index	3,069	98.3	11.1	75.6	131.3
Rain, Snow, & Humidity					
Annual Precipitation	3,069	38.2	14.1	3.5	118.2
Annual Precipitation Days	3,069	94.1	24.6	13.3	198.0
Annual Snowfall (inches)	3,069	26.9	34.1	0	334.9
Annual Snow Days	3,069	12.7	13.7	0	90.0
Annual Days with Snow ≥ 5"	3,069	0.5	1.7	0	20.9
Annual Days with Snow ≥ 10"	3,069	0.1	0.6	0	10.4
July Daily Relative Humidity	3,069	65.7	9.6	23.8	82.0
Coast/River/Topography Control Variables					
Ocean Coast Dummy	389	1	0	1	1
Great Lakes Dummy	170	1	0	1	1
Major River Dummy	1,153	1	0	1	1
log(1+Ocean Shoreline/sq.km)	235	0.07	0.07	0.00	0.50
log(1+Great Lakes Shoreline/sq.km)	84	0.04	0.03	0.00	0.17
Topography (Linear)	3,069	0.09	0.14	0	3.11

*Change in log density shown on annual percentage basis (i.e., divided by number of years and then multiplied by 100). Summary statistics are for all continental U.S. counties. Weather variables are averages based on 1961-to-1990 data purchased from www.climatesource.com. For dummy variables and shoreline measures, summary statistics are shown only for observations with values that do not equal zero.

Table 3: 2000 Population Density Level and Single Weather Elements

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Winter Weather	**January Daily Mean Temp**	**January Daily Minimum Temp**	**January Daily Maximum Temp**	**Annual Extreme Minimum Temp**	**Annual Cold Temp Days**	**Annual Heating Degree Days**	
Linear	***0.0241***	***0.0332***	***0.0153***	***0.0278***	***-0.0085***	***-0.0001***	
	(0.0042)	***(0.0042)***	***(0.0042)***	***(0.0034)***	***(0.0009)***	***(0.0000)***	
Quadratic	***-0.0008***	***-0.0008***	***-0.0007***	***-0.0009***	***-9.4E-5***	***-4.9E-8***	
	(0.0003)	***(0.0003)***	***(0.0003)***	***(0.0002)***	***(1.8E-5)***	***(9.2E-9)***	
R^2	0.047	0.081	0.024	0.097	0.134	0.091	
Maximum Density Implied at	**46˚F** **(7˚F)**	40˚F (8˚F)	**52˚F** **(6˚F)**	**12˚F** **(5˚F)**	**68** **(10)**	**3,874** **(394)**	
Summer Weather	**July Daily Mean Temp**	**July Daily Minimum Temp**	**July Daily Maximum Temp**	**Annual Extreme Maximum Temp**	**Annual Hot Temp Days**	**Annual Cooling Degree Days**	**July Daily Heat Index**
Linear	0.0007	***0.0286***	***-0.0385***	***-0.0836***	***-0.0070***	***0.0002***	0.0046
	(0.0098)	***(0.0087)***	***(0.0107)***	***(0.0116)***	***(0.0021)***	***(0.0001)***	(0.0046)
Quadratic	***-0.0063***	***-0.0037***	***-0.0067***	***-0.0116***	3.2E-5	*-1.3E-7*	***-0.0016***
	(0.0012)	***(0.0008)***	***(0.0014)***	***(0.0015)***	(3.8E-5)	*(7.0E-8)*	***(0.0004)***
R^2	0.047	0.0756	0.040	0.112	0.019	0.010	0.021
Maximum Density Implied at	**75˚F** **(1˚F)**	**67˚F** **(2˚F)**	**85˚F** **(1˚F)**	**94˚F** **(0˚F)**			**100˚F** **(1˚F)**
Rain, Snow, & Humidity	**Annual Precip**	**Annual Precip Days**	**Annual Snowfall**	**Annual Snow Days**	**Annual Days with Snow >= 5"**	**Annual Days with Snow >= 10"**	**July Daily Relative Humidity**
Linear	***0.0460***	***0.0259***	***-0.0061***	-0.0096	***-0.1296***	***-0.6744***	***0.0869***
	(0.0032)	***(0.0020)***	***(0.0023)***	(0.0060)	***(0.0450)***	***(0.1240)***	***(0.0073)***
Quadratic	***-0.0012***	***-0.0003***	-9.8E-6	-0.0001	0.0012	***0.0656***	***0.0014***
	(0.0001)	***(0.0000)***	(1.5E-5)	(0.0002)	(0.0034)	***(0.0224)***	***(0.0004)***
R^2	0.252	0.210	0.028	0.014	0.020	0.032	0.224
Maximum Density Implied at	**58″** **(2″)**	**145** **(8)**				**5 (Min)** **(1)**	34% (Min) (7%)

Table shows results from regressing log(1+2000 Population Density) on a constant, the weather variable, and the weather variable minus its sample mean squared. Number of observations is 3,069 for all regressions. Standard errors in parentheses are robust to spatial correlation using the Conley spatial estimator discussed in the text with a weighting that declines quadratically to zero for counties with centers 200 km apart. Bold type signifies coefficients statistically different from zero at the 0.05 level; italic type signifies coefficients statistically different from zero at the 0.10 level. "Implies Maximum Density" is implied value at which population density is maximized; it is included only if quadratic coefficient statistically differs from zero at 0.05 level. "(Min)" superscript signifies density is minimized at implied value. Standard error in parentheses is constructed using the "delta" method. Bold type for implied values signifies that point estimate plus or minus two standard deviations is within observed sample values.

Table 4: 2000 Population Density Level and Dual Weather Elements

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Winter Weather Variable →	**January Daily Mean Temp**	**January Daily Minimum Temp**	**January Daily Maximum Temp**	**Annual Extreme Minimum Temp**	**Annual Cold Temp Days**	**Annual Heating Degree Days**	**January Daily Minimum Temp**
Summer Weather Variable →	**July Daily Mean Temp**	**July Daily Maximum Temp**	**July Daily Maximum Temp**	**Annual Extreme Maximum Temp**	**Annual Hot Temp Days**	**Annual Cooling Degree Days**	**July Daily Heat Index**
Winter Linear	***0.0553***	***0.0702***	***0.0547***	***0.0379***	***-0.0260***	***-0.0005***	***0.0802***
	(0.0059)	***(0.0049)***	***(0.0052)***	***(0.0031)***	***(0.0014)***	***(0.0001)***	***(0.0063)***
Winter Quadratic	-0.0001	***-0.0005***	*-0.0004*	***-0.0007***	***-3.9E-5***	***-2.7E-8***	*0.0004*
	(0.0003)	***(0.0002)***	*(0.0002)*	***(0.0002)***	***(1.4E-5)***	***(1.2E-8)***	*(0.0002)*
Summer Linear	***-0.0958***	***-0.1393***	***-0.1374***	***-0.1244***	***-0.0417***	***-0.0014***	***-0.0541***
	(0.0145)	***(0.0136)***	***(0.0153)***	***(0.0101)***	***(0.0030)***	***(0.0002)***	***(0.0066)***
Summer Quadratic	***-0.0111***	***-0.0103***	***-0.0104***	***-0.0102***	***0.0002***	***2.9E-7***	***-0.0033***
	(0.0013)	***(0.0013)***	***(0.0014)***	***(0.0013)***	***(0.0000)***	***(8.2E-8)***	***(0.0003)***
R^2	0.136	0.240	0.147	0.251	0.419	0.157	0.194

Table shows results from regressing log(1+2000 Population Density) on a constant, the two weather variables, and the two weather variables minus their sample means squared. Number of observations is 3,069 for all regressions. Standard errors in parentheses are robust to spatial correlation using the Conley spatial estimator discussed in the text with a weighting that declines quadratically to zero for counties with centers 200 km apart. Bold type signifies coefficients statistically different from zero at the 0.05 level; italic type signifies coefficients statistically different from zero at the 0.10 level.

Table 5: 2000 Population and Employment Density with Multiple Weather Elements

Dependent Vairable → / Independent Variables ↓		(1)	(2)	(3)	(4)	(5)	(6)
		log(1+2000 Population Density)			log(1+2000 Employment Density)		
Coast/River/Topography Controls		**No**	**Yes**	**Yes**	**No**	**Yes**	**Yes**
Census Division Dummies		**No**	**No**	**Yes**	**No**	**No**	**Yes**
Cold Temp Days	linear	***-0.0288***	***-0.0228***	***-0.0302***	***-0.0268***	***-0.0203***	***-0.0282***
		(0.0018)	***(0.0021)***	***(0.0019)***	***(0.0018)***	***(0.0021)***	***(0.0020)***
	quadratic	-1.9E-5	***-4.7E-5***	*-2.4E-5*	-1.3E-5	***-4.4E-5***	-1.8E-5
		(1.3E-5)	***(1.6E-5)***	*(1.3E-5)*	(1.3E-5)	***(1.6E-5)***	(1.3E-5)
Hot Temp Days	linear	***-0.0444***	***-0.0345***	***-0.0347***	***-0.0426***	***-0.0323***	***-0.0334***
		(0.0028)	***(0.0027)***	***(0.0029)***	***(0.0028)***	***(0.0027)***	***(0.0030)***
	quadratic	***1.5E-4***	***1.2E-4***	4.1E-5	***1.3E-4***	***1.1E-4***	2.4E-5
		(3.3E-5)	***(3.2E-5)***	(2.9E-5)	***(3.2E-5)***	***(3.0E-5)***	(2.8E-5)
Annual Precip	linear	***-0.0077***	-0.0032	***-0.0105***	***-0.0131***	***-0.0081***	***-0.0155***
		(0.0038)	(0.0038)	***(0.0036)***	***(0.0037)***	***(0.0038)***	***(0.0036)***
	quadratic	***-0.0009***	***-0.0010***	***-0.0007***	***-0.0008***	***-0.0009***	***-0.0006***
		(0.0001)	***(0.0001)***	***(0.0001)***	***(0.0001)***	***(0.0001)***	***(0.0001)***
Observations		3,069	3,069	3,069	3,069	3,069	3,069
Number of Indep. Variables		6	13	21	6	13	21
R^2		0.464	0.500	0.539	0.385	0.424	0.463
Control Variables R^2		-	0.189	0.388	-	0.179	0.333

Table shows results from regressing listed dependent variable on the enumerated weather variables, control variables, and a constant. Quadratic weather variables have had their respective sample means subtracted. Standard errors in parentheses are robust to spatial correlation using the Conley spatial estimator discussed in the text with a weighting that declines quadratically to zero for counties with centers 200 km apart. Bold type signifies coefficients statistically different from zero at the 0.05 level; italic type signifies coefficients statistically different from zero at the 0.10 level.

Table 6: Population Growth, 1960–2000, and Single Weather Elements

Winter Weather	(1) January Daily Mean Temp	(2) January Daily Minimum Temp	(3) January Daily Maximum Temp	(4) Annual Extreme Minimum Temp	(5) Annual Cold Temp Days	(6) Annual Heating Degree Days	(7)
Linear	***0.0309***	***0.0342***	***0.0271***	***0.0265***	***-0.0057***	***-0.0001***	
	(0.0038)	***(0.0040)***	***(0.0036)***	***(0.0031)***	***(0.0009)***	***(0.0000)***	
Quadratic	***0.0006***	***0.0006***	*0.0005*	***0.0004***	***6.5E-5***	***2.5E-8***	
	(0.0003)	***(0.0003)***	*(0.0003)*	***(0.0002)***	***(1.5E-5)***	***(8.2E-9)***	
R^2	0.111	0.125	0.095	0.122	0.099	0.074	
Implies Minimum Growth	3˚F	-6˚F		-36˚F	**157**	**7,776**	
	(13˚F)	(11˚F)		(14˚F)	**(12)**	**(827)**	

Summer Weather	July Daily Mean Temp	July Daily Minimum Temp	July Daily Maximum Temp	Annual Extreme Maximum Temp	Annual Hot Temp Days	Annual Cooling Degree Days	July Daily Heat Index
Linear	***0.0198***	***0.0278***	0.0065	***-0.0333***	0.0008	0.0001	0.0049
	(0.0090)	***(0.0082)***	(0.0090)	***(0.0102)***	(0.0015)	(0.0001)	(0.0039)
Quadratic	***0.0037***	***0.0036***	***0.0026***	-0.0008	***9.4E-5***	***3.1E-7***	***0.0010***
	(0.0009)	***(0.0007)***	***(0.0011)***	(0.0014)	***(3.6E-5)***	***(7.1E-8)***	***(0.0003)***
R^2	0.021	0.036	0.008	0.015	0.016	0.063	0.015
Implies Minimum Growth	**73˚F**	**59˚F**	**86˚F**		**38**	**1,091**	**96˚F**
	(1˚F)	**(1˚F)**	**(2˚F)**		**(9)**	**(112)**	**(2˚F)**

Rain, Snow, & Humidity	Annual Precip	Annual Precip Days	Annual Snowfall	Annual Snow Days	Annual Days with Snow >= 5"	Annual Days with Snow >= 10"	July Daily Relative Humidity
Linear	***0.0172***	***0.0059***	***-0.0066***	***-0.0235***	***0.0954***	***0.3033***	***0.0343***
	(0.0030)	***(0.0018)***	***(0.0020)***	***(0.0046)***	***(0.0357)***	***(0.0915)***	***(0.0077)***
Quadratic	0.0000	-2.9E-5	***0.0001***	***0.0008***	-0.0039	***-0.0349***	***0.0020***
	(0.0001)	(4.0E-5)	***(0.0000)***	***(0.0001)***	(0.0026)	***(0.0126)***	***(0.0004)***
R^2	0.046	0.016	0.022	0.046	0.009	0.008	0.047
Implies Minimum Growth			**80˝**	**28**		**4 (Max)**	**57% (Max)**
			(9˝)	**(2)**		**(1)**	**(1%)**

Table shows results from regressing ([log(1+2000 Pop Density)-log(1+1960 Pop Density)]×100/40) on a constant, the weather variable, and the weather variable minus its sample mean squared. Number of observations is 3,063 for all regressions. Standard errors in parentheses are robust to spatial correlation using the Conley spatial estimator discussed in the text with a weighting that declines quadratically to zero for counties with centers 200 km apart. Bold type signifies coefficients statistically different from zero at the 0.05 level; italic type signifies coefficients statistically different from zero at the 0.10 level. "Implies Minimum Growth" is implied value at which population density growth is minimized; it is included only if quadratic coefficient statistically differs from zero at 0.05 level. "(Max)" superscript signifies growth is maximized at implied value. Standard error in parentheses is constructed using the "delta" method. Bold type for implied values signifies that point estimate plus or minus two standard deviations is within observed weather values.

Table 7: Population Growth, 1960–2000, and Dual Weather Elements

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Winter Weather Variable →	**January Daily Mean Temp**	**January Daily Minimum Temp**	**January Daily Maximum Temp**	**Annual Extreme Minimum Temp**	**Annual Cold Temp Days**	**Annual Heating Degree Days**	**January Daily Minimum Temp**
Summer Weather Variable →	**July Daily Mean Temp**	**July Daily Maximum Temp**	**July Daily Maximum Temp**	**Annual Extreme Maximum Temp**	**Annual Hot Temp Days**	**Annual Cooling Degree Days**	**July Daily Heat Index**
Winter Linear	***0.0606***	***0.0525***	***0.0545***	***0.0339***	***-0.0120***	***-0.0005***	***0.0689***
	(0.0052)	***(0.0044)***	***(0.0048)***	***(0.0029)***	***(0.0012)***	***(0.0001)***	***(0.0051)***
Winter Quadratic	***0.0008***	***0.0006***	***0.0005***	***0.0005***	***8.7E-5***	***3.5E-8***	***0.0012***
	(0.0002)	***(0.0002)***	***(0.0002)***	***(0.0002)***	***(1.5E-5)***	***(1.0E-8)***	***(0.0002)***
Summer Linear	***-0.0913***	***-0.0700***	***-0.0962***	***-0.0731***	***-0.0147***	***-0.0013***	***-0.0463***
	(0.0124)	***(0.0098)***	***(0.0123)***	***(0.0086)***	***(0.0018)***	***(0.0001)***	***(0.0049)***
Summer Quadratic	***-0.0025***	-0.0009	-0.0019	-5.0E-6	4.4E-5	***3.9E-7***	***-0.0009***
	(0.0011)	(0.0011)	(0.0012)	(1.2E-3)	(3.1E-5)	***(7.7E-8)***	***(0.0003)***
R^2	0.188	0.185	0.179	0.189	0.157	0.181	0.216

Table shows results from regressing ([log(1+2000 Pop Density)-log(1+1960 Pop Density)]×100/40) on a constant, the two weather variables, and the two weather variables minus their sample means squared. Number of observations is 3,063 for all regressions. Standard errors in parentheses are robust to spatial correlation using the Conley spatial estimator discussed in the text with a weighting that declines quadratically to zero for counties with centers 200 km apart. Bold type signifies coefficients statistically different from zero at the 0.05 level; italic type signifies coefficients statistically different from zero at the 0.10 level.

Table 8: Population Growth, 1960–2000, and Multiple Weather Elements

Dependent Vairable → / Independent Variables ↓		(1)	(2)	(3)	(4)	(5)
		∆log(1+Population Density)				
Coast/River/Topography Controls		**No**	**Yes**	**Yes**	**Yes**	**Yes**
Initial Density Spline		**No**	**No**	**Yes**	**Yes**	**Yes**
Concentric Total Population		**No**	**No**	**Yes**	**Yes**	**Yes**
Census Division Dummies		**No**	**No**	**No**	**Yes**	**No**
State Dummies		**No**	**No**	**No**	**No**	**Yes**
January Daily Max Temp	linear	***0.0653***	***0.0531***	***0.0504***	***0.0469***	***0.0405***
		(0.0065)	***(0.0069)***	***(0.0063)***	***(0.0075)***	***(0.0096)***
	quadratic	***0.0014***	***0.0013***	***0.0015***	***0.0018***	***0.0013***
		(0.0003)	***(0.0002)***	***(0.0003)***	***(0.0003)***	***(0.0003)***
July Daily Heat Index	linear	***-0.0536***	***-0.0385***	***-0.0357***	***-0.0287***	***-0.0252***
		(0.0073)	***(0.0085)***	***(0.0081)***	***(0.0088)***	***(0.0093)***
	quadratic	***-0.0009***	***-0.0010***	-0.0003	-0.0004	-0.0004
		(0.0004)	***(0.0003)***	(0.0003)	(0.0003)	(0.0004)
July Relative Humidity	linear	***-0.0340***	***-0.0406***	***-0.0573***	***-0.0616***	***-0.0438***
		(0.0097)	***(0.0097)***	***(0.0107)***	***(0.0116)***	***(0.0122)***
	quadratic	-0.0002	-0.0002	***-0.0007***	***-0.0010***	***-0.0008***
		(0.0004)	(0.0004)	***(0.0003)***	***(0.0003)***	***(0.0004)***
Annual Precip	linear	***0.0189***	***0.0209***	***0.0149***	***0.0183***	*0.0120*
		(0.0072)	***(0.0072)***	***(0.0067)***	***(0.0073)***	*(0.0065)*
	quadratic	***-3.5E-4***	***-3.6E-4***	-2.0E-5	-4.7E-5	3.7E-5
		(1.5E-4)	***(1.5E-4)***	(1.2E-4)	(1.2E-4)	(1.2E-4)
Annual Precip Days	linear	0.0061	0.0049	0.0028	0.0023	0.0063
		(0.0038)	(0.0039)	(0.0039)	(0.0044)	(0.0042)
	quadratic	***-1.7E-4***	***-1.7E-4***	***-2.1E-4***	***-1.7E-4***	***-1.9E-4***
		(5.5E-5)	***(5.2E-5)***	***(4.3E-5)***	***(4.1E-5)***	***(4.5E-5)***
Observations		3,063	3,063	3,063	3,063	3,063
Number of Indep. Variables		10	17	31	39	79
R^2		0.239	0.263	0.385	0.396	0.456
Control Variables R^2		-	0.120	0.271	0.324	0.432

Table shows results from regressing ([log(1+2000 Pop Density)-log(1+1960 Pop Density)]×100/40) on the enumerated weather variables, control variables, and a constant. Quadratic weather variables have had their respective sample mean subtracted. Standard errors in parentheses are robust to spatial correlation using the Conley spatial estimator discussed in the text with a weighting that declines quadratically to zero for counties with centers 200 km apart. Bold type signifies coefficients statistically different from zero at the 0.05 level; italic type signifies coefficients statistically different from zero at the 0.10 level.

Table 9: Population Growth and the Weather by Decade

Δlog(1+Pop Density for Years)→ Independent Variables ↓		(1) 1900–1910	(2) 1910–1920	(3) 1920–1930	(4) 1930–1940	(5) 1940–1950	(6) 1950–1960	(7) 1960–1970	(8) 1970–1980	(9) 1980–1990	(10) 1990–2000
Coast/River/Topog Controls		**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Initial Density Spline		**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Concentric Total Population		**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
January Daily Max Temp	linear	−0.0094	0.0043	**0.0529**	**0.0385**	**0.0600**	**0.0610**	**0.0298**	**0.0731**	**0.0491**	**0.0436**
		(0.0147)	(0.0100)	**(0.0131)**	**(0.0066)**	**(0.0080)**	**(0.0088)**	**(0.0068)**	**(0.0083)**	**(0.0069)**	**(0.0067)**
	quadratic	−0.0009	0.0003	**0.0012**	**0.0009**	**0.0013**	**0.0032**	**0.0018**	**0.0014**	**0.0019**	**0.0006**
		(0.0006)	(0.0005)	**(0.0005)**	**(0.0003)**	**(0.0003)**	**(0.0004)**	**(0.0003)**	**(0.0004)**	**(0.0003)**	**(0.0002)**
July Daily Heat Index	linear	**0.0740**	0.0199	**−0.0297**	**−0.0473**	**−0.0493**	**−0.0480**	**−0.0348**	**−0.0451**	**−0.0374**	**−0.0272**
		(0.0180)	(0.0122)	**(0.0137)**	**(0.0083)**	**(0.0109)**	**(0.0105)**	**(0.0082)**	**(0.0111)**	**(0.0096)**	**(0.0091)**
	quadratic	−0.0007	**−0.0011**	*−0.0010*	−0.0004	**−0.0021**	**−0.0023**	−0.0005	0.0001	−0.0003	0.0003
		(0.0007)	**(0.0005)**	*(0.0006)*	(0.0004)	**(0.0004)**	**(0.0004)**	(0.0004)	(0.0005)	(0.0004)	(0.0003)
July Relative Humidity	linear	*0.0465*	**0.0406**	0.0155	*0.0213*	*−0.0208*	**−0.0807**	**−0.0705**	**−0.0702**	**−0.0617**	**−0.0329**
		(0.0243)	**(0.0177)**	(0.0200)	*(0.0109)*	*(0.0124)*	**(0.0140)**	**(0.0122)**	**(0.0142)**	**(0.0117)**	**(0.0109)**
	quadratic	−0.0004	0.0003	**−0.0013**	**0.0008**	−0.0002	**−0.0015**	**−0.0012**	*−0.0007*	**−0.0009**	−0.0002
		(0.0006)	(0.0005)	**(0.0006)**	**(0.0003)**	(0.0004)	**(0.0005)**	**(0.0004)**	*(0.0004)*	**(0.0003)**	(0.0003)
Annual Precip	linear	**−0.0310**	*−0.0214*	−0.0114	*0.0133*	**−0.0360**	**−0.0260**	**0.0294**	0.0069	**0.0162**	0.0007
		(0.0132)	*(0.0116)*	(0.0095)	*(0.0069)*	**(0.0100)**	**(0.0099)**	**(0.0080)**	(0.0092)	**(0.0073)**	(0.0078)
	quadratic	−0.0003	0.0000	0.0000	−0.0001	**0.0008**	**0.0009**	−0.0002	0.0000	0.0000	**0.0004**
		(0.0003)	(0.0002)	(0.0002)	(0.0001)	**(0.0002)**	**(0.0002)**	(0.0002)	(0.0002)	(0.0001)	**(0.0001)**
Annual Precip Days	linear	**0.0201**	0.0073	**−0.0122**	−0.0019	*0.0087*	**0.0109**	−0.0039	*0.0108*	−0.0053	0.0024
		(0.0074)	(0.0063)	**(0.0057)**	(0.0037)	*(0.0044)*	**(0.0055)**	(0.0045)	*(0.0059)*	(0.0044)	(0.0042)
	quadratic	**0.0004**	*0.0001*	**0.0003**	*−0.0001*	0.0000	**−0.0003**	**−0.0001**	**−0.0003**	**−0.0001**	**−0.0003**
		(0.0001)	*(0.0001)*	**(0.0001)**	*(0.0000)*	(0.0001)	**(0.0001)**	**(0.0001)**	**(0.0001)**	**(0.0000)**	**(0.0000)**
Observations		2,696	2,845	3,014	3,060	3,062	3,064	3,063	3,067	3,067	3,069
Number of Indep. Variables		31	31	31	31	31	31	31	31	31	31
R^2		0.311	0.149	0.257	0.195	0.414	0.460	0.350	0.329	0.402	0.331
Control Variables R^2		0.249	0.127	0.169	0.114	0.341	0.382	0.305	0.209	0.281	0.235

Table shows results from regressing Δlog(1+Population Density)×100/10 for given years on enumerated weather variables, control variables, and a constant. Quadratic weather variables have had their respective sample mean subtracted. Standard errors in parentheses are robust to spatial correlation using the Conley spatial estimator discussed in the text with a weighting that declines quadratically to zero for counties with centers 200 km apart. Bold type signifies coefficients statistically different from zero at the 0.05 level; italic type signifies coefficients statistically different from zero at the 0.10 level.

Table 10: Working Age and Seniors Population Growth, 1960–2000

Dependent Vairable → / Independent Variables ↓		(1)	(2)	(3)	(4)	(5)	(6)
		Δlog(1+ Working Age Pop Density)			Δlog(1+ Seniors Pop Density)		
Coast/River/Topog Controls		**No**	**Yes**	**Yes**	**No**	**Yes**	**Yes**
Initial Density Spline		**No**	**No**	**Yes**	**No**	**No**	**Yes**
Concentric Total Population		**No**	**No**	**Yes**	**No**	**No**	**Yes**
January Daily Max Temp	linear	***0.0647***	***0.0531***	***0.0507***	***0.0642***	***0.0496***	***0.0432***
		(0.0064)	***(0.0068)***	***(0.0061)***	***(0.0047)***	***(0.0052)***	***(0.0044)***
	quadratic	***0.0013***	***0.0012***	***0.0013***	***0.0014***	***0.0013***	***0.0014***
		(0.0002)	***(0.0002)***	***(0.0002)***	***(0.0002)***	***(0.0002)***	***(0.0002)***
July Daily Heat Index	linear	***-0.0512***	***-0.0369***	***-0.0349***	***-0.0461***	***-0.0277***	***-0.0227***
		(0.0072)	***(0.0084)***	***(0.0080)***	***(0.0054)***	***(0.0064)***	***(0.0060)***
	quadratic	***-0.0009***	***-0.0010***	-0.0003	***-0.0018***	***-0.0019***	***-0.0011***
		(0.0003)	***(0.0003)***	(0.0003)	***(0.0002)***	***(0.0002)***	***(0.0002)***
July Relative Humidity	linear	***-0.0209***	***-0.0262***	***-0.0428***	0.0050	-0.0050	***-0.0206***
		(0.0095)	***(0.0096)***	***(0.0105)***	(0.0074)	(0.0071)	***(0.0067)***
	quadratic	-0.0001	-0.0001	*-5.6E-4*	7.8E-6	3.5E-5	*-3.6E-4*
		(0.0004)	(0.0004)	*(3.0E-4)*	(2.8E-4)	(2.5E-4)	*(1.9E-4)*
Annual Precip	linear	***0.0163***	***0.0183***	*0.0113*	0.0011	0.0033	0.0015
		(0.0071)	***(0.0072)***	*(0.0064)*	(0.0052)	(0.0048)	(0.0043)
	quadratic	***-3.2E-4***	***-3.3E-4***	1.2E-5	-1.2E-4	-1.4E-4	***1.6E-4***
		(1.4E-4)	***(1.4E-4)***	(1.2E-4)	(9.7E-5)	(9.0E-5)	***(8.1E-5)***
Annual Precip Days	linear	***0.0074***	0.0059	0.0035	***0.0090***	***0.0087***	0.0047
		(0.0037)	(0.0038)	(0.0037)	***(0.0029)***	***(0.0028)***	(0.0029)
	quadratic	***-1.8E-4***	***-1.8E-4***	***-2.2E-4***	***-1.1E-4***	***-1.0E-4***	***-1.3E-4***
		(5.5E-5)	***(5.3E-5)***	***(4.2E-5)***	***(3.9E-5)***	***(3.5E-5)***	***(2.5E-5)***
Observations		3,063	3,063	3,063	3,063	3,063	3,063
Number of Indep. Variables		10	17	31	10	17	31
R^2		0.250	0.273	0.419	0.328	0.372	0.582
Control Variables R^2		-	0.125	0.314	-	0.195	0.475

Table shows results from regressing ([log(1+2000 Age-Specific Pop Density)-log(1+1960 Age-Specific Pop Density)]×100/40) on the enumerated weather variables, control variables, and a constant. For Columns 1 to 3, the dependent variable is measured for persons 21 to 64 years old. For Columns 4 to 6, the dependent variable is measured for persons 65 and older. Quadratic weather variables have had their respective sample mean subtracted. Standard errors in parentheses are robust to spatial correlation using the Conley spatial estimator discussed in the text with a weighting that declines quadratically to zero for counties with centers 200 km apart. Bold type signifies coefficients statistically different from zero at the 0.05 level; italic type signifies coefficients statistically different from zero at the 0.10 level.

Supplemental Table 1: The Spread of Air Conditioning

	Percent of Households with Any Air Conditioning			Percent of Households with Central Air Conditioning			Percent of New Housing Units with Central Air Conditioning		
	1960	1970	1980	1960	1970	1980	1960	1970	1980
UNITED STATES	**12.5**	**37.1**	**56.2**	**1.9**	**11.0**	**27.8**	**4.7**	**27.7**	**52.7**
Alabama	17.0	50.2	72.4	2.7	15.6	38.0	7.2	35.2	62.9
Alaska	0.8	1.1	0.9	0.0	0.6	0.6	0.0	0.7	0.6
Arizona	27.3	54.8	72.0	15.6	42.2	64.0	25.0	58.1	74.7
Arkansas	17.1	49.9	73.2	2.6	15.9	40.0	7.7	35.5	65.0
California	10.0	25.4	40.1	2.5	8.8	22.4	4.6	17.4	44.4
Colorado	6.3	17.5	31.6	1.9	6.0	15.6	3.0	13.1	24.7
Connecticut	6.6	26.7	47.6	0.7	2.4	7.5	1.8	6.3	19.7
Delaware	16.3	49.1	66.1	1.1	13.5	30.9	2.1	29.6	55.8
Dist. of Columbia	19.8	50.8	68.6	5.6	19.6	33.6	29.0	60.9	79.6
Florida	17.5	61.6	84.4	2.5	23.1	55.7	4.3	43.1	81.9
Georgia	14.3	45.2	67.2	1.6	16.4	40.8	3.8	34.5	66.5
Hawaii	2.3	11.8	16.7	0.0	0.5	4.3	0.0	1.2	9.9
Idaho	7.6	18.2	33.4	2.0	6.8	17.4	2.9	13.5	27.8
Illinois	13.6	45.7	67.8	1.7	11.4	32.2	4.4	26.4	60.8
Indiana	9.8	33.6	60.2	1.5	10.5	31.0	2.5	25.8	56.6
Iowa	12.3	38.1	67.6	1.2	11.2	33.5	3.7	32.2	61.5
Kansas	29.9	61.5	80.8	4.9	18.7	46.9	13.8	48.8	81.2
Kentucky	8.5	32.8	63.3	0.8	8.3	29.7	1.9	21.1	50.1
Louisiana	24.0	61.7	83.7	3.7	21.2	47.0	9.3	49.8	78.1
Maine	2.8	2.6	11.6	0.7	0.4	0.9	2.4	0.4	1.8
Maryland	15.7	54.1	71.4	2.1	25.5	43.5	4.9	63.4	76.4
Massachusetts	5.3	19.7	37.9	0.5	1.6	5.1	1.8	6.1	15.4
Michigan	4.9	20.4	35.6	0.8	4.6	14.4	1.5	11.7	29.1
Minnesota	6.6	31.1	50.2	0.9	5.5	19.4	2.7	11.4	31.6
Mississippi	14.6	50.6	71.7	1.5	14.9	34.8	3.7	35.7	56.8
Missouri	17.6	50.2	72.5	2.7	19.4	42.9	7.7	45.2	69.2
Montana	4.2	10.3	20.8	2.0	3.3	8.6	4.0	7.9	15.6
Nebraska	22.8	56.4	79.2	3.7	21.7	48.9	11.7	55.1	81.1
Nevada	15.3	59.1	70.6	10.8	45.6	56.2	17.6	59.5	64.6
New Hampshire	3.0	10.8	24.7	0.5	1.3	2.4	0.0	2.9	5.0
New Jersey	17.1	48.5	66.2	0.8	7.5	19.5	2.0	21.3	48.0
New Mexico	7.9	35.3	61.9	3.2	20.0	44.0	4.8	31.1	58.4
New York	10.8	32.0	42.5	0.5	3.3	7.3	1.6	12.3	19.2
North Carolina	8.8	34.9	61.6	1.2	9.5	31.6	3.2	19.7	52.9
North Dakota	2.3	12.2	41.3	0.6	2.6	13.7	1.6	4.8	23.3
Ohio	7.1	25.5	48.2	1.0	6.9	22.2	2.2	18.5	46.8
Oklahoma	29.7	63.2	83.5	3.8	20.7	46.5	10.5	53.4	77.5
Oregon	6.0	10.2	19.7	2.1	2.9	8.4	2.6	5.6	14.3
Pennsylvania	10.0	29.7	42.7	0.9	4.5	12.2	2.8	16.7	31.2
Rhode Island	4.0	15.2	33.0	0.0	1.0	3.5	0.0	2.9	9.7
South Carolina	10.8	43.5	69.5	1.5	12.7	36.6	4.6	26.0	58.1
South Dakota	5.6	29.3	61.1	1.5	7.7	25.9	4.2	18.4	40.3
Tennessee	19.8	54.1	75.5	2.1	11.9	33.6	5.0	28.1	58.9
Texas	30.6	66.9	84.7	5.4	29.0	55.9	11.6	63.5	85.0
Utah	8.0	26.9	50.3	1.9	11.4	31.5	2.6	22.4	45.2
Vermont	1.9	4.9	9.9	0.0	0.8	0.7	0.0	1.1	1.1
Virginia	12.3	48.5	66.4	1.4	19.3	39.1	3.1	44.0	64.3
Washington	4.2	7.2	15.1	2.2	2.9	7.0	4.3	4.1	11.9
West Virginia	5.7	19.1	40.0	0.9	4.1	14.5	2.9	12.7	24.9
Wisconsin	6.0	22.0	38.7	1.0	3.9	12.5	1.6	8.6	20.7
Wyoming	5.3	11.2	20.5	0.9	3.4	7.3	2.8	8.5	11.3

"Any Air Conditioning" includes both window units and central. "New Housing Units" are housing units constructed in previous 10 years. Data derived from Ruggles and Sobek et. al. (1997)

Supplemental Table 2: The Spread of Modern Heating

	Percent of Households Heated by Utility-Supplied Natural Gas or Electricity						
	1940	1950	1960	1970	1980	1990	2000
UNITED STATES	**11.3**	**27.3**	**44.9**	**62.9**	**71.5**	**76.8**	**81.6**
Alabama	3.2	21.5	53.7	68.7	73.6	77.4	84.0
Alaska	NA	NA	0.3	30.8	50.1	54.6	56.1
Arizona	20.7	58.7	82.0	91.0	91.0	90.9	91.8
Arkansas	14.7	33.6	55.4	69.4	73.5	75.5	81.2
California	67.1	82.9	90.2	94.6	94.0	92.4	92.3
Colorado	7.5	47.6	76.2	88.3	91.2	89.9	91.0
Connecticut	1.1	6.6	13.0	25.8	32.3	41.4	43.6
Delaware	0.8	6.0	14.1	34.5	39.4	52.3	62.4
Dist. of Columbia	10.8	27.9	36.3	58.1	67.6	84.0	89.6
Florida	3.1	11.9	20.3	47.7	71.8	86.3	93.2
Georgia	4.2	21.7	51.5	69.8	75.6	80.5	87.2
Hawaii	NA	NA	1.3	3.4	8.6	41.2	51.0
Idaho	0.1	1.9	13.8	42.0	65.8	68.0	79.9
Illinois	2.2	12.5	36.2	73.5	89.1	91.5	93.0
Indiana	0.9	7.6	27.0	62.9	77.3	82.4	86.3
Iowa	2.5	12.8	41.9	64.7	73.1	76.1	80.1
Kansas	27.6	60.8	77.1	85.3	87.7	87.7	88.7
Kentucky	5.9	22.4	47.2	66.3	73.9	75.6	83.2
Louisiana	29.2	57.8	79.8	87.8	91.2	91.3	93.7
Maine	0.2	1.7	2.2	3.7	12.1	13.5	7.9
Maryland	2.5	12.3	31.9	51.7	59.8	72.8	79.1
Massachusetts	1.2	7.7	15.7	32.1	42.4	51.5	56.3
Michigan	3.8	19.1	46.2	72.6	80.8	82.3	84.9
Minnesota	3.1	15.6	39.4	56.5	66.3	73.4	79.7
Mississippi	9.4	28.0	50.6	63.4	69.0	71.4	77.0
Missouri	4.7	24.7	51.7	70.7	76.7	78.5	82.0
Montana	25.6	43.8	62.3	73.4	75.5	72.1	75.1
Nebraska	7.0	29.8	60.3	75.1	81.5	83.8	86.6
Nevada	0.7	19.7	48.0	73.6	84.1	87.0	92.1
New Hampshire	0.4	1.9	6.4	15.3	25.2	27.6	26.0
New Jersey	1.4	9.5	24.9	44.5	52.1	67.5	77.2
New Mexico	20.9	51.8	70.1	80.6	82.5	79.2	79.3
New York	3.0	19.4	23.0	39.6	44.4	54.2	60.5
North Carolina	0.1	1.6	5.8	25.7	45.3	60.6	73.0
North Dakota	2.7	7.6	17.6	35.1	57.8	65.9	71.9
Ohio	7.4	34.4	67.7	79.9	84.0	85.0	87.1
Oklahoma	45.1	68.6	77.6	84.0	85.8	84.9	86.6
Oregon	2.4	9.2	24.6	53.4	66.3	69.3	83.1
Pennsylvania	4.4	20.4	37.2	52.2	59.2	64.3	67.8
Rhode Island	1.2	6.9	16.4	30.1	39.2	48.6	53.9
South Carolina	0.2	3.0	10.4	36.0	56.9	71.5	84.6
South Dakota	5.3	12.5	28.7	43.4	56.4	60.8	68.1
Tennessee	3.3	17.5	47.8	73.0	77.6	80.5	88.2
Texas	43.1	65.6	79.4	87.0	89.3	90.6	92.6
Utah	9.4	35.0	69.8	84.6	91.1	91.4	94.6
Vermont	0.1	0.6	0.7	10.9	16.1	17.1	16.9
Virginia	0.4	5.1	18.7	39.3	55.3	69.0	77.7
Washington	0.8	4.9	19.4	53.8	74.6	77.5	85.8
West Virginia	29.9	48.4	62.4	73.4	77.7	76.0	79.9
Wisconsin	0.5	4.5	22.5	51.2	63.3	70.3	77.8
Wyoming	26.0	52.2	69.0	79.5	84.7	79.4	82.1

1940 to 1990 data based on U.S. Census Bureau (1999). 2000 data based on 2000 Decennial Census, Summary File 3.

Supplemental Table 3: Correlation among Weather Variables

Winter Weather	Jan Mean Temp	Jan Min Temp	Jan Max Temp	Extreme Min Temp	Cold Temp Days	Heating Deg Days
Jan Mean Temp	1					
Jan Min Temp	0.989	1				
Jan Max Temp	0.991	0.960	1			
Extreme Min Temp	0.975	0.983	0.949	1		
Cold Temp Days	-0.924	-0.936	-0.895	-0.936	1	
Heating Deg Days	-0.957	-0.944	-0.950	-0.935	0.967	1

Summer Weather	July Mean Temp	July Min Temp	July Max Temp	Extreme Max Temp	Hot Temp Days	Cooling Deg Days	July Heat Index	July Rel Humidity
July Mean Temp	1							
July Min Temp	0.970	1						
July Max Temp	0.949	0.843	1					
Extreme Max Temp	0.758	0.619	0.870	1				
Hot Temp Days	0.843	0.743	0.896	0.750	1			
Cooling Deg Days	0.904	0.880	0.853	0.605	0.927	1		
July Heat Index	0.956	0.917	0.920	0.705	0.898	0.947	1	
July Rel Humidity	0.270	0.467	-0.008	-0.218	-0.051	0.252	0.293	1

Supplemental Table 3: Correlation among Weather Variables (2 of 2)

Rain & Snow	Annual Precip	Precip Days	Annual Snowfall	Snow Days	5" Snow Days	10" Snow Days	July Rel Humidity
Annual Precip	1						
Precip Days	0.651	1					
Annual Snowfall	-0.270	0.302	1				
Snow Days	-0.334	0.368	0.930	1			
5" Snow Days	-0.051	0.245	0.875	0.670	1		
10" Snow Days	-0.045	0.106	0.716	0.477	0.859	1	
July Rel Humidity	0.759	0.593	-0.332	-0.259	-0.272	-0.306	1

Mixed	Jan Max Temp	Cold Temp Days	July Heat Index	Hot Temp Days	Annual Precip	Precip Days	Annual Snowfall	July Rel Humidity
Jan Max Temp	1							
Cold Temp Days	-0.895	1						
July Heat Index	0.781	-0.824	1					
Hot Temp Days	0.816	-0.754	0.898	1				
Annual Precip	0.410	-0.572	0.321	0.071	1			
Precip Days	-0.204	0.060	-0.368	-0.555	0.651	1		
Annual Snowfall	-0.586	0.727	-0.749	-0.598	-0.270	0.302	1	
July Rel Humidity	0.156	-0.415	0.293	-0.051	0.759	0.593	-0.332	1

Supplemental Table 4: Regression for Fitted 2000 Population Density

Dependent Vairable → Independent Variables ↓	log(1+2000 Population Density)	
Coast/River/Topography Controls	**Yes**	
Winter Variables:	Linear	Quadratic
Extreme Minimum Temperature	***0.0742***	0.0005
	(0.0115)	(0.0003)
January Daily Maximum Temperature	***-0.0793***	0.0006
	(0.0265)	(0.0005)
Annual Heating Degree Days	***-0.0005***	***-4.0E-8***
	(0.0003)	***(2.1E-8)***
Summer Variables:	Linear	Quadratic
Annual Hot Temperature Days	***-0.0582***	***0.0003***
	(0.0069)	***(0.0001)***
Annual Cooling Degree Days	***0.0018***	***-5.2E-7***
	(0.0005)	***(1.6E-7)***
July Daily Relative Humidity	***-0.0375***	***-0.0011***
	(0.0109)	***(0.0003)***
Rain and Snow Variables:	Linear	Quadratic
Annual Precipitation Days	-0.0006	***-0.0002***
	(0.0035)	***(0.0000)***
Annual Snowfall	***-0.0142***	***4.8E-5***
	(0.0055)	***(2.2E-5)***
Annual Snow Days	***0.0915***	***-0.0009***
	(0.0153)	***(0.0002)***
Observations	3,069	
Number of Indep. Variables	25	
R^2	0.551	
Control Variables R^2	0.189	

Table shows results from regressing listed dependent variable on the enumerated weather variables, control variables, and a constant. Quadratic weather variables have had their respective sample mean subtracted. Standard errors in parentheses are robust to spatial correlation using the Conley spatial estimator discussed in the text with a weighting that declines quadratically to zero for counties with centers 200 km apart. Bold type signifies coefficients statistically different from zero at the 0.05 level; italic type signifies coefficients statistically different from zero at the 0.10 level.

Supplemental Table 5: Population and Employment Growth, 1970–2000, and Multiple Weather Elements

Dependent Vairable → Independent Variables ↓		(1)	(2)	(3)	(4)	(5)	(6)
		log(1+Pop Density 2000)– log(1+Pop Density 1970)			log(1+Emp Density 2000)– log(1+Emp Density 1970)		
Coast/River/Topography Controls		**No**	**Yes**	**Yes**	**No**	**Yes**	**Yes**
Initial Pop or Emp Density Spline		**No**	**No**	**Yes**	**No**	**No**	**Yes**
Concentric Total Pop or Emp		**No**	**No**	**Yes**	**No**	**No**	**Yes**
January Daily Max Temp	linear	***0.0703***	***0.0629***	***0.0555***	***0.0580***	***0.0414***	***0.0394***
		(0.0065)	***(0.0071)***	***(0.0066)***	***(0.0076)***	***(0.0079)***	***(0.0069)***
	quadratic	***0.0012***	***0.0012***	***0.0014***	***0.0014***	***0.0014***	***0.0013***
		(0.0002)	***(0.0002)***	***(0.0003)***	***(0.0003)***	***(0.0003)***	***(0.0003)***
July Daily Heat Index	linear	***-0.0554***	***-0.0449***	***-0.0359***	***-0.0613***	***-0.0372***	***-0.0364***
		(0.0088)	***(0.0099)***	***(0.0090)***	***(0.0080)***	***(0.0095)***	***(0.0089)***
	quadratic	-0.0001	-0.0002	-0.0001	***-0.0008***	***-0.0010***	-0.0001
		(0.0004)	(0.0003)	(0.0003)	***(0.0004)***	***(0.0004)***	(0.0003)
July Relative Humidity	linear	***-0.0449***	***-0.0486***	***-0.0527***	*-0.0194*	***-0.0297***	***-0.0410***
		(0.0095)	***(0.0099)***	***(0.0109)***	*(0.0107)*	***(0.0108)***	***(0.0114)***
	quadratic	-0.0001	0.0000	*-0.0005*	-0.0004	-0.0003	***-0.0009***
		(0.0003)	(0.0003)	*(0.0003)*	(0.0004)	(0.0004)	***(0.0003)***
Annual Precip	linear	0.0071	0.0074	0.0100	***0.0236***	***0.0242***	***0.0148***
		(0.0069)	(0.0071)	(0.0067)	***(0.0082)***	***(0.0084)***	***(0.0072)***
	quadratic	0.0001	0.0001	0.0001	***-0.0005***	***-0.0005***	-0.0001
		(0.0001)	(0.0001)	(0.0001)	***(0.0002)***	***(0.0002)***	(0.0001)
Annual Precip Days	linear	0.0042	0.0040	0.0031	0.0018	0.0024	-0.0008
		(0.0045)	(0.0046)	(0.0042)	(0.0041)	(0.0043)	(0.0040)
	quadratic	***-2.4E-4***	***-2.4E-4***	***-2.3E-4***	***-1.4E-4***	***-1.4E-4***	***-1.8E-4***
		(4.6E-5)	***(4.6E-5)***	***(4.1E-5)***	***(6.2E-5)***	***(5.8E-5)***	***(4.4E-5)***
Observations		3,067	3,067	3,067	3,067	3,067	3,067
Number of Indep. Variables		10	17	31	10	17	31
R^2		0.286	0.293	0.392	0.157	0.183	0.354
Control Variables R^2		-	0.073	0.262	-	0.103	0.304

Table shows results from regressing ([log(1+2000 Density)-log(1+1970 Density)]×100/30) on the enumerated weather variables, control variables, and a constant. Initial density spline and concentric total control variables measure either population or employment corresponding to the dependent variable. Quadratic weather variables have had their respective sample mean subtracted. Standard errors in parentheses are robust to spatial correlation using the Conley spatial estimator discussed in the text with a weighting that declines quadratically to zero for counties with centers 200 km apart. Bold type signifies coefficients statistically different from zero at the 0.05 level; italic type signifies coefficients statistically different from zero at the 0.10 level.

Supplemental Table 6: Regression for Fitted 1960–2000 Population Growth

Dependent Vairable → Independent Variables ↓	∆log(1+Pop Density)	
Coast/River/Topography Controls	**Yes**	
Initial Density Spline	**Yes**	
Concentric Total Population	**Yes**	
Winter Variables:	Linear	Quadratic
January Daily Minimum Temperature	***0.0817***	***0.0022***
	(0.0224)	***(0.0007)***
January Daily Maximum Temperature	***0.1298***	0.0009
	(0.0185)	(0.0007)
Annual Heating Degree Days	***0.0011***	*-4.0E-8*
	(0.0002)	*(2.4E-8)*
Summer Variables:		
Extreme Maximum Temperature	***-0.0706***	***-0.0081***
	(0.0263)	***(0.0020)***
July Daily Maximum Temperature	***0.3077***	***0.0118***
	(0.0738)	***(0.0023)***
July Daily Heat Index	-0.0360	***-0.0014***
	(0.0296)	***(0.0006)***
Annual Hot Temperature Days	***-0.0288***	*1.0E-4*
	(0.0077)	*(5.4E-5)*
July Daily Relative Humidity	***-0.0351***	***-0.0008***
	(0.0150)	***(0.0003)***
Rain and Snow Variables:		
Annual Precipitation	***0.0172***	0.0000
	(0.0068)	(0.0001)
Annual Precipitation Days	-0.0040	***-0.0002***
	(0.0037)	***(0.0001)***
Annual Snow Days	-0.0091	***0.0004***
	(0.0093)	***(0.0002)***
Observations	3,063	
Number of Indep. Variables	43	
R^2	0.429	
Control Variables R^2	0.271	

Table shows results from regressing ([log(1+2000 Pop Density)-log(1+1960 Pop Density)]×100/40) on the enumerated weather variables, control variables, and a constant. Quadratic weather variables have had their respective sample mean subtracted. Standard errors in parentheses are robust to spatial correlation using the Conley spatial estimator discussed in the text with a weighting that declines quadratically to zero for counties with centers 200 km apart. Bold type signifies coefficients statistically different from zero at the 0.05 level; italic type signifies coefficients statistically different from zero at the 0.10 level.

Supplemental Table 7: Ranking Cities' Weather (1 of 2)

Urbanized Area	*Places Rated* Rank	Fitted Level Rank	Fitted Growth Rank	Jan Max Temp	Cold Temp Days	July Heat Index	July Rel Humid	Hot Temp Days	Annual Precip	Precip Days	Annual Snow
Santa Barbara, CA	1	36	21	64°	3	79°	63%	9	17″	28	0″
San Diego, CA	2	20	17	67°	7	84°	67%	24	12″	36	0″
Los Angeles, CA	3	50	22	67°	8	92°	63%	41	15″	30	0″
Riverside-San Bernardino, CA	4	94	8	66°	17	104°	48%	90	14″	33	0″
San Francisco-Oakland, CA	5	53	34	56°	14	82°	68%	20	23″	56	0″
Bakersfield, CA	6	91	10	57°	18	104°	34%	108	6″	29	0″
San Jose, CA	7	64	33	58°	18	90°	70%	25	19″	49	0″
Phoenix, AZ	8	96	2	66°	18	114°	31%	165	9″	33	0″
Sacramento, CA	9	88	27	53°	22	105°	51%	80	20″	53	0″
Fresno, CA	10	92	7	54°	27	107°	39%	106	11″	38	0″
Miami-Hialeah, FL	11	7	1	76°	0	107°	76%	58	58″	121	0″
Tampa-St. Ptrsburg-Clrwater, FL	12	45	4	70°	3	110°	76%	92	49″	96	0″
Medford, OR	13	95	19	46°	93	95°	56%	49	20″	92	5″
Reno, NV	14	99	9	44°	183	90°	39%	41	11″	47	35″
Las Vegas, NV	15	100	3	58°	55	107°	20%	138	4″	23	0″
Orlando, FL	16	68	6	71°	4	115°	77%	105	50″	101	0″
Tucson, AZ	17	93	5	66°	31	114°	43%	147	13″	48	0″
Jacksonville, FL	18	34	16	65°	16	114°	78%	68	51″	103	0″
Boise City, ID	19	72	40	37°	128	91°	36%	47	11″	73	20″
Gainesville, FL	20	80	20	67°	18	113°	76%	99	52″	108	0″
Corpus Christi, TX	21	73	32	64°	5	116°	76%	101	31″	66	0″
Tallahassee, FL	22	87	41	62°	34	114°	79%	85	63″	108	0″
El Paso, TX-NM	23	98	25	58°	76	105°	44%	109	9″	41	2″
Greensboro, NC	24	39	51	47°	86	101°	74%	32	44″	105	10″
Houston, TX	25	52	23	61°	17	115°	71%	92	48″	86	0″
Albuquerque, NM	26	97	18	48°	132	97°	41%	63	9″	53	10″
Seattle, WA	27	61	28	45°	48	78°	66%	3	40″	148	6″
Columbus, GA-AL	28	65	46	56°	46	113°	74%	73	51″	98	0″
New Orleans, LA	29	44	26	62°	15	114°	78%	76	60″	100	0″
Baton Rouge, LA	30	63	37	60°	27	113°	76%	83	61″	104	0″
Charlotte, NC	31	37	42	50°	72	104°	72%	41	45″	102	4″
Augusta, GA-SC	32	83	47	55°	59	112°	73%	70	47″	96	0″
Austin, TX	33	77	29	59°	27	117°	64%	108	33″	71	0″
Raleigh, NC	34	43	53	50°	74	104°	75%	39	44″	104	5″
New York-N. New Jersey, NY-NJ	35	16	52	37°	110	91°	69%	14	47″	106	26″
Atlanta, GA	36	29	35	50°	70	101°	73%	35	54″	103	1″
Baltimore, MD	37	25	54	41°	98	98°	69%	30	44″	104	17″
Norfolk-VA Beach-Nwprt News, VA	38	13	44	48°	62	99°	73%	29	46″	103	8″
Columbia, SC	39	70	49	55°	53	112°	73%	70	48″	102	0″
Spokane, WA	40	22	39	34°	133	85°	42%	22	18″	98	34″
Mobile, AL	41	47	30	60°	23	111°	76%	73	64″	105	0″
Portland-Vancouver, OR-WA	42	66	38	46°	48	82°	62%	13	43″	145	4″
Birmingham, AL	43	57	43	52°	63	108°	73%	57	57″	100	0″
San Antonio, TX	44	86	24	62°	27	117°	64%	114	31″	67	0″
Richmond, VA	45	46	59	46°	94	102°	73%	38	43″	100	16″
Salt Lake City, UT	46	67	15	37°	130	92°	35%	45	15″	73	49″
Boulder, CO	47	60	11	44°	146	91°	49%	27	17″	78	71″
Boston, MA	48	35	61	35°	135	88°	72%	10	46″	113	50″
Colorado Springs, CO	49	85	13	42°	171	86°	49%	19	16″	74	48″
Knoxville, TN	50	21	57	46°	80	100°	75%	25	50″	117	9″

Weather variables based on data from www.climatesource.com

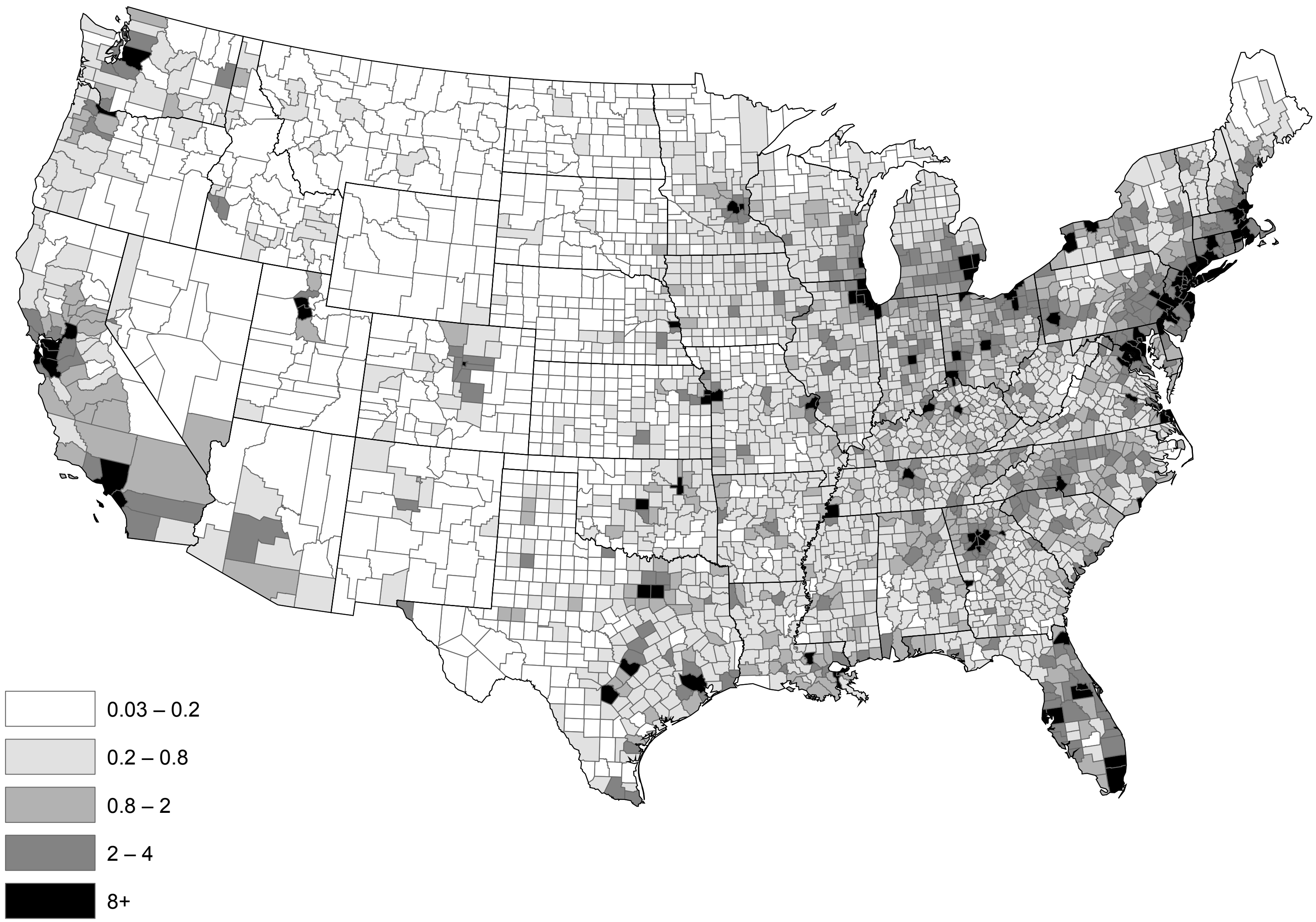
Supplemental Table 7: Ranking Cities' Weather (2 of 2)

Urbanized Area	*Places Rated* Rank	Fitted Level Rank	Fitted Growth Rank	Jan Max Temp	Cold Temp Days	July Heat Index	July Rel Humid	Hot Temp Days	Annual Precip	Precip Days	Annual Snow
Philadelphia, PA-NJ	51	23	55	38°	108	95°	69%	23	45″	103	22″
Washington, DC-MD-VA	52	41	63	42°	101	99°	73%	31	41″	101	18″
Providence-Pawtucket, RI-MA	53	31	58	36°	130	87°	72%	8	47″	111	36″
Shreveport, LA	54	76	48	55°	45	115°	70%	86	48″	88	0″
Charleston, WV	55	18	93	42°	109	96°	74%	23	43″	132	24″
Denver, CO	56	78	14	44°	153	90°	50%	29	16″	70	60″
Jackson, MS	57	89	64	56°	52	116°	76%	83	56″	97	0″
Little Rock-North Little Rock, AR	58	62	82	49°	62	113°	72%	69	51″	93	5″
Pittsburgh, PA	59	6	88	35°	123	89°	69%	10	38″	134	29″
Dallas-Fort Worth, TX	60	79	36	54°	45	114°	60%	97	36″	70	0″
Louisville, KY-IN	61	17	70	41°	93	99°	70%	32	45″	109	14″
Portland, ME	62	59	78	31°	155	84°	74%	6	45″	117	70″
Columbus, OH	63	9	76	35°	122	92°	67%	15	39″	116	23″
Nashville, TN	64	55	66	45°	87	104°	71%	47	49″	110	8″
Hartford-Middletown, CT	65	28	50	35°	135	89°	69%	12	46″	107	36″
Memphis, TN-AR-MS	66	49	45	47°	63	109°	69%	63	52″	95	3″
Cheyenne, WY	67	38	12	38°	175	85°	50%	11	15″	83	51″
Cincinnati, OH-KY	68	19	77	37°	117	95°	70%	23	42″	115	19″
Tulsa, OK	69	75	60	46°	86	111°	62%	71	39″	74	7″
Oklahoma City, OK	70	71	56	48°	80	111°	60%	76	34″	72	7″
Rochester, NY	71	10	89	31°	134	85°	70%	8	32″	140	86″
Detroit, MI	72	2	81	30°	134	88°	67%	12	32″	113	35″
Toledo, OH-MI	73	12	100	31°	125	93°	72%	23	33″	110	32″
Billings, MT	74	69	31	34°	160	90°	44%	35	15″	78	56″
St. Louis, MO-IL	75	40	83	38°	109	103°	69%	42	39″	93	18″
Bangor, ME	76	81	69	27°	164	82°	72%	5	41″	118	80″
Kansas City, MO-KS	77	32	67	38°	107	101°	63%	41	39″	82	17″
Wichita, KS	78	74	84	40°	110	107°	59%	64	31″	73	15″
Indianapolis, IN	79	14	86	34°	126	94°	72%	19	40″	110	23″
Akron, OH	80	1	99	32°	120	87°	71%	7	38″	134	41″
Dayton, OH	81	5	80	35°	116	93°	66%	21	39″	115	24″
Buffalo-Niagara Falls, NY	82	3	85	31°	134	84°	67%	3	38″	147	86″
Syracuse, NY	83	27	94	30°	141	86°	70%	7	40″	153	100″
Cleveland, OH	84	4	97	32°	129	87°	70%	7	38″	136	51″
Chicago, IL-Northwestern Indiana	85	15	92	30°	132	90°	66%	18	36″	108	34″
Milwaukee, WI	86	26	96	26°	146	87°	70%	12	32″	105	41″
Lincoln, NE	87	56	95	33°	137	101°	65%	43	29″	76	23″
Fort Wayne, IN	88	11	79	31°	135	91°	68%	14	36″	109	33″
Bismarck, ND	89	90	75	20°	187	89°	61%	22	16″	81	32″
Omaha, NE-IA	90	42	98	31°	140	97°	67%	32	30″	84	25″
Fargo-Moorhead, ND-MN	91	58	65	16°	180	89°	66%	15	20″	87	38″
Burlington, VT	92	24	90	26°	155	85°	69%	6	33″	135	69″
Albany-Schenectady-Troy, NY	93	30	71	31°	145	90°	71%	10	37″	118	58″
Des Moines, IA	94	33	91	28°	137	94°	68%	23	33″	94	23″
Grand Rapids, MI	95	8	74	29°	148	87°	69%	9	36″	127	68″
Sioux Falls, SD	96	51	87	25°	167	94°	65%	26	24″	89	37″
Madison, WI	97	54	72	25°	162	89°	68%	11	31″	100	33″
Minneapolis-St. Paul, MN	98	48	68	22°	164	90°	66%	14	30″	96	44″
Manchester, NH	99	82	62	32°	162	87°	72%	9	40″	115	59″
Duluth, MN-WI	100	84	73	19°	177	80°	72%	3	29″	109	58″

Weather variables based on data from www.climatesource.com

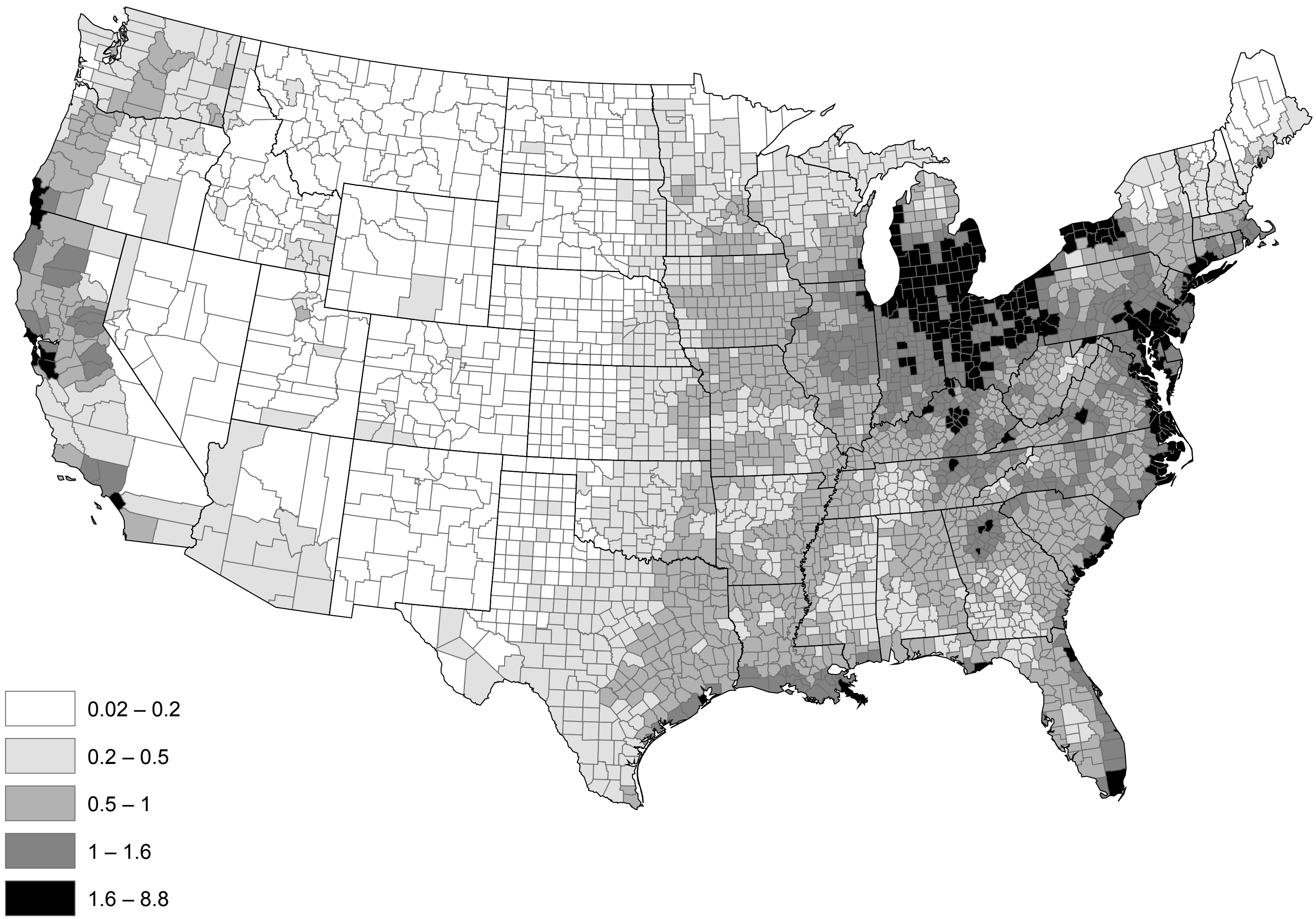
Map 1: Relative Population Density

(1+2000 county pop. density)/(1+2000 U.S. pop. density)



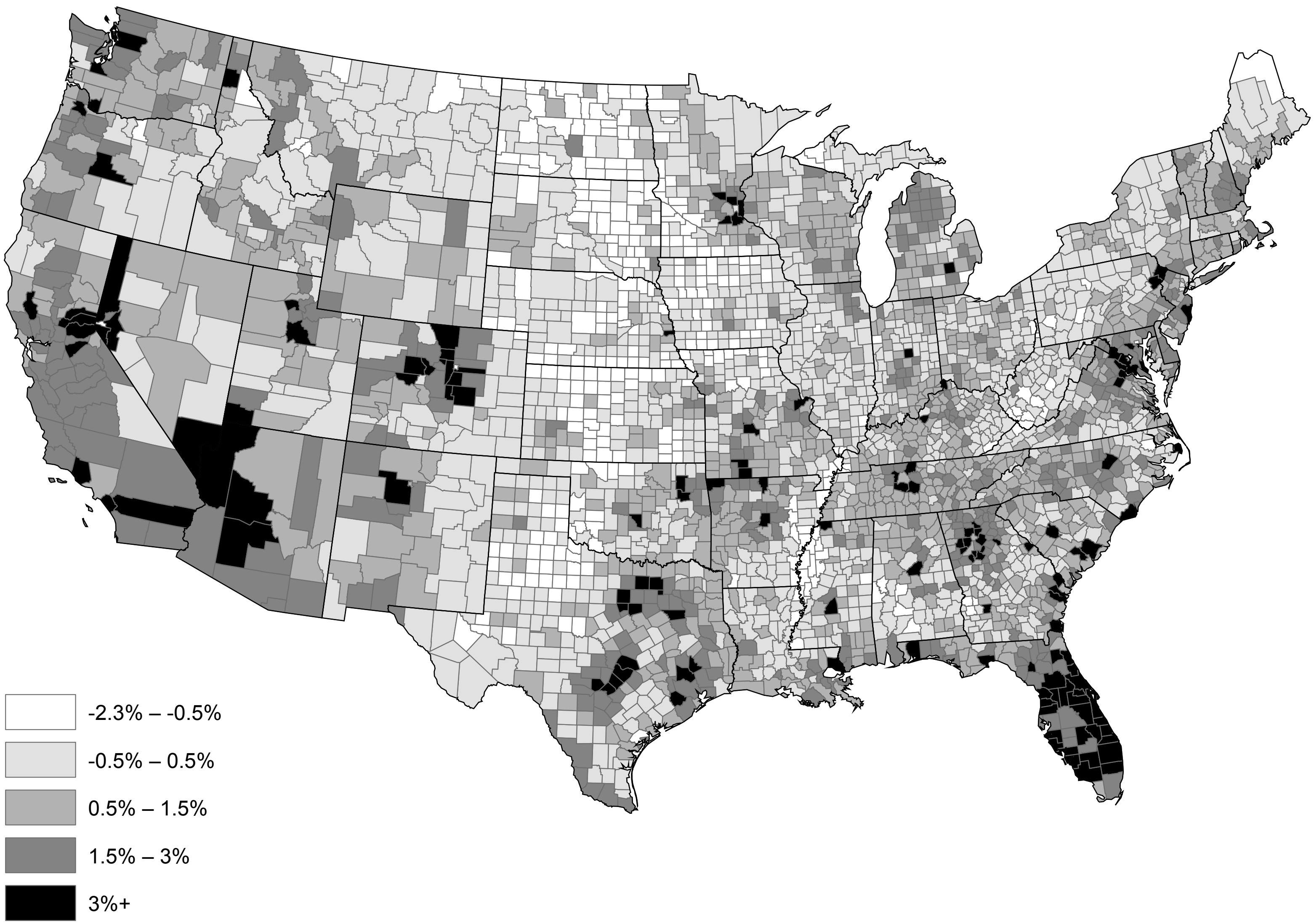
Map 2: Expected Population Density from Weather

(Fitted (1+2000 pop. density) controlling for coast & topography))/(1+2000 U.S. pop. density)



Map 3: Population Growth, 1960–2000

Annual growth rate of (1+population density)



Map 4: Expected Population Growth from Weather, 1960–2000

Fitted annual growth rate of (1+pop. density) controlling for coast, topography, initial density and concentric pop.