Moving to Nice Weather

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Abstract

U.S. residents have been moving en masse to places with nice weather. Well known is the migration towards places with warm winters, which is often attributed to the introduction of air conditioning. But people have also been moving to places with cooler, less-humid summers, which is the opposite of what is expected from the introduction of air conditioning. Nor can the movement to nice weather be primarily explained by shifting industrial composition or by elderly migration. Instead, a large portion of weather-related moves appear to be the result of an increased valuation of nice weather as a consumption amenity, probably due to broad-based rising per capita income.

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1 Introduction

Over the course of the twentieth century, U.S. residents moved en masse to places with nice weather. Well known is the migration towards places with warm winters, 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. Nor can the movement to nice weather be attributed primarily to elderly retirement, as the trend is nearly as strong among working-age individuals. Instead, regressions of population growth on weather and other characteristics suggest that a large portion of weather-related moves have followed from a broad-based increase in valuation of nice weather as a consumption amenity. If so, other consumption amenities are also likely to have served as important sources of local growth. Moreover, if increased valuations are the result of rising per capita income, then the migration to nice weather is likely to continue.

Valuing weather's contribution to quality-of-life has received considerable attention in the compensating differential literature. The value of a weather characteristic can be calculated as the sum of the wages a household is willing to forego plus the price premium they are willing to pay to live in a place with that characteristic (Rosen, 1979; Roback, 1982). Based on public use micro-samples 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; and one inch less precipitation, from -$58 to $34 (Blomquist, Berger, and Hoehn, 1988; Gyourko and Tracy, 1991; and Stover and Leven, 1992). More recent research finds that Italian households are similarly willing to pay substantial sums to enjoy less precipitation and more moderate summer temperatures (Maddison and Biggano, 2003). Other recent research finds a substantial increase in U.S. households' valuation of weather's contribution to quality-of-life during the latter part of the twentieth century (Cragg and Kahn, 1999; Costa and Kahn, 2003).

There are several important limitations to the compensating differential methodology of valuing weather. First is that the number of U.S. geographic observations is relatively small since the necessary micro data is available only for places with a population of at least 100,000. These observations are subject to a sharp selection bias in that places where large numbers of people have not chosen to live are excluded. A second limitation of the compensating differential methodology is the imprecision of estimated values due to the difficulty controlling for individual-specific and house-specific characteristics (Gyourko, Tracy, and Kahn, 1999; Combes, Duranton, and Laurent, 2004; Lee, 2005). To the extent that higher-income individuals disproportionately desire to live in high quality-of-life locations, there will be a strong positive correlation between local consumption amenities and respondents' unobserved characteristics. A third limitation is the identifying assumption that the system of localities across which attributes are being valued is at its long run steady state. But the high persistence of population flows across these localities establishes that this is almost certainly not the case (Greenwood et. al., 1991; Rappaport 2004a).

In contrast to the price approach of the compensating differential literature, the present paper pursues a "quantity" approach. Partial correlations of population growth with local weather reflect changes in the valuation of weather's combined contributions to quality-of-life and productivity. Continental U.S. counties are used as the geographic unit of observation. The large number of these—more than three thousand—allow for high statistical power. The discrete partition of the continental United States captures an extremely wide variation in weather. And the underlying theory explicitly takes into account that steady-state and actual population are likely to differ.

There are three main limitations to the quantity approach. First is that it can generally capture only *changes* in contributions to quality-of-life and productivity. Second is that it does not quantify the size of the changed contributions. Third is that it fails to distinguish between changed contributions to quality-of-life versus changed contributions to productivity.

The paper proceeds as follows: Sections 2 and 3 respectively discuss the paper's theoretical and econometric framework. Section 4 briefly describes the data. Section 5 reports and interprets the empirical results. A last section concludes.

2 Theory

Two sets of theory underpin the papers empirics. The first concerns how to interpret partial correlations between local population growth and exogenous attributes. The second considers some specific ways in which the weather's contribution to quality-of-life and productivity has changed over the past century.

2.1 The Determinants of Local Population

The theoretical framework for inferring the determinants of local population follows Haurin (1980) and Rappaport (2004a, 2004b). The world is assumed to be composed of a large number of "localities." These are fixed geographic areas where people both live and work and across which there is at least moderate factor mobility. Localities *exogenously* differ with respect to some attributes that affect local quality-of-life and local productivity. Local attributes that affect quality-of-life enter directly as arguments in individuals' utility functions. Those that affect productivity enter directly as arguments in firms' profit functions. Equivalently, quality-of-life attributes shift individuals' indifference curves over wages and prices. Productivity attributes shift firms' iso-profit curves over wages and other input prices.

In a long-run steady state, population density is an increasing function of local quality-of-life and local productivity. The intuition is simple. Individuals are willing to endure greater crowdedness and the associated higher price of housing in order to directly enjoy higher quality-of-life and to indirectly enjoy higher productivity via the higher wages it affords. Indeed, varying local population density is the primary mechanism forcing local wages and housing prices to adjust such that utility and profits can be equated across localities.

The setup might suggest that a "level" regression of population density on exogenous attributes can identify contributions to quality-of-life and productivity. But this is unlikely to be so. One reason is that factor mobility is not perfect. Another is that productivity and quality-of-life also depend on endogenous attributes.

Imperfect factor mobility implies that current population density may differ substantially from steady-state population density. Even relatively small frictions to labor and capital mobility can cause population to require several decades to transition from one steady state to another (Rappaport, 2004a). Hence a positive partial correlation between current population density and an exogenous attribute may reflect a past rather than a present contribution to quality-of-life and productivity.

The additional difficulty introduced by the dependence of quality-of-life and productivity on endogenous attributes is that such attributes are likely to be correlated with the exogenous ones. Substantial research suggests that quality-of-life and productivity depend themselves on population size and density. Size and density may increase quality-of-life by allowing for increased social interaction and product variety (e.g., Glaeser, Kolko, Saiz, 2001; Fujita and Thisse, 2002; Compton and Pollak, 2004). They may increase productivity via local scale economies (e.g., Henderson et. al., 1995; Ciccone and Hall, 1996; Henderson, 2003). An exogenous attribute that increased quality-of-life and productivity in the past may no longer do so in the present. But the high population density caused by the past contribution may cause *steady-state* population density to remain correlated with the attribute via a "lock-in effect" from self-reinforcing agglomeration forces (Fujita and Mori, 1996).

Interpreting partial correlations between population growth and exogenous attributes is more straightforward. Regardless of factor mobility, an exogenous attribute that is partially correlated with long-run population growth will be partially correlated with a change in steady-state density. Imperfect factor mobility simply implies that the change may have occurred substantially before the period over which population growth is being measured. One possible cause of a change in steady-state density is a change in contribution from the exogenous attribute to quality-of-life and productivity. Another is a change in contribution to these from an endogenous attribute that is correlated with the exogenous attribute. To rule out the latter possibility, regressions can include controls for predetermined endogenous attributes.

2.2 The Changing Contributions from Weather

That the weather contributes to quality-of-life and productivity is obvious. Indeed it is hard to think of any outdoor activity—whether for leisure or for work—that is not affected by the weather. But for present purposes, the relevant question is how the weather's contribution to quality-of-life and productivity has changed over the past century? Among many possible ways, four stand out. The first is that the decline of agricultural employment has decreased the importance of weather characteristics that contribute to agricultural productivity. The second is that air-conditioning and improved heating technology have decreased the disutility from extreme temperatures. The third is that rising per capita income has increased the relative valuation of temperate weather. The fourth is that it is primarily the growing number of affluent and mobile retirees who have increased their valuation of temperate weather.

The explanation based on agriculture's declining employment is straightforward. Agricultural productivity clearly depends on numerous weather attributes such as rain and the length of a growing season. While this dependence may have remained largely unchanged over the course of the twentieth century, the importance of agricultural productivity to overall U.S. productivity has become much smaller. Agriculture's share of U.S. employment fell from approximately 40 percent in 1900 to less than 2 percent in 2000. The sector's relative decline effectively freed up more than a third of U.S. residents and jobs to relocate based on considerations other than agricultural productivity. A related possibility is that relative employment declines in the minerals extraction and manufacturing industries freed up people to move away from bad-weather places where such industries were concentrated.

The roles of air-conditioning and improved heating technology require a bit more explanation. As a matter of background, the first known air-conditioning units were installed around 1900. Over the subsequent 40 years, AC was slowly adopted by manufacturers and a few service businesses. However, it was not until after World War 2 that the mass adoption of residential air-conditioning began. As late as 1960, only 13 percent of U.S. households had any sort of AC and only 2 percent had central AC. Home heating improved over the course of the 20th-century first as vendor-delivered oil came to supplant coal as the primary fuel source starting in the 1920s. In turn, utility-supplied natural gas and electricity came to supplant oil starting in the 1940s. During the latter part of the century, there were also considerable improvements in home insulation technologies.[1]

To help understand the implications of air-conditioning and improved heating, Figure 1 shows average daily high summer and winter temperatures for 45 U.S. urbanized areas. The summer measure is a discomfort index reflecting both temperature and humidity. More

[1]Tables documenting the incidence of air-conditioning and primary heating fuel across states and decades are included in the paper's supplemental materials.

details on the weather variables are in the data-description section below. The solid lines in the figure represent a possible set of indifference curves prior to AC and improved heating. Utility is decreasing as you move to the lower right. The underlying loss function assumes 75°F to be the year-round ideal.[2]

The introduction of air-conditioning lessens the disutility from hot summer weather. Individuals become willing to endure more of it in return for warm winter weather. Equivalently, the indifference curves stretch rightward along the top vertical axis. This causes numerous preference reversals. For example, Duluth Minnesota's weather without air conditioning is preferred to that of numerous cities in the South and Southwest. But with AC, Duluth's weather is the least preferred of the depicted cities. Similarly, numerous cities in the bottom left of the figure reverse from having relatively desirable to relatively undesirable weather.

Restoring spatial equilibrium requires a new vector of wages and house prices across places. In general, the more the valuation of a place's weather has risen, the larger the required fall in its relative wage and increase in its relative house price. Migration is the mechanism that brings the new spatial equilibrium about. People will move both towards places with hot summers and towards places with warm winters (that is, towards the upper right of the figure). The impulse towards hot summers is intuitive: hot weather has become "less bad". The impulse towards warm winters arises because AC increases the sensitivity of relative weather valuations to winter temperatures. This is reflected in the flatter indifference curves.[3] Reinforcing the faster relative growth of cities with warm winters is the strong positive correlation between summer and winter temperatures.

Improved heating technologies cause indifference curves to shift in a way that mirrors the shift from air-conditioning. Specifically, the curves stretch downward along the left vertical

[2]Specifically, the loss function is assumed to be of the form, $L = a\,|s - s^*|^{\alpha} + b\,|w - w^*|^{\beta}$. Here s and w are respectively summer and winter temperature. The remaining elements of the equation are positive parameters. The introduction of AC is depicted as a decrease in a. Improved heating might correspond to a decrease in b. An increased valuation of nice weather might correspond to *increases* in both a and b.

[3]An illustrative example, in the upper middle of Figure 1, is the required faster relative growth of Riverside compared to Bakersfield, notwithstanding that the two cities' summer weather is virtually identical. Prior to AC, the two cities' weather bundles were equally valued. With AC, Riverside's weather is preferred to that of Bakersfield.

axis. As a result, people move both towards places with cold winters and towards places with cool summers (that is, towards the lower left of the figure).

Although air-conditioning and improved heating imply migration in the opposite direction, the two technological changes in combination only partially offset each other. With approximately equal magnitude shifts from air-conditioning and from improved heating, the AC-induced impulse toward warm winters and the heating-induced impulse towards cool summers are indeed cancelled out. But there continues to be a combined impulse toward cold winters and hot summers. To see this, suppose that the combined technological shocks cause indifference curves to shift downward and rightward such that the new curves exactly parallel the old ones. As a result of such a shift, the required compensating variation for any given deviation from ideal weather falls. Restoring spatial equilibrium thus requires people to move in the same direction as the shift in indifference curves.

In sharp contrast to the implied movement from air-conditioning and improved heating, the rise in income associated with broad-based technological progress creates an impulse for people to move toward places with nicer weather. Over the course of the 20th-century, rising total factor productivity and the implied capital accumulation increased U.S. per capita income more than six-fold (Maddison 1995). Since nice weather is a normal good, demand for it should have risen as well. More specifically, increased consumption of goods is associated with a decrease in marginal utility. Hence people should be willing to pay a higher price, in terms of foregone consumption, to live in a place with nice weather. In terms of Figure 1, rising incomes cause indifference curves to shift inward: a given loss occurs at a smaller deviation from ideal weather. Maintaining spatial equilibrium thus requires places with nice weather to have an increasingly negative wage premium and an increasingly positive house price premium.

Migration to nice weather places can help bring the new spatial equilibrium about by putting downward pressure on wages and upward pressure on house prices. But rising incomes also cause other demand shifts that make the direction of migration ambiguous. In particular, demand for housing also increases. The resulting broad-based rise in house prices—both because technological progress may disproportionately apply to non-housing goods and because production of housing tends to be intensive in non-reproducible land—can actually induce movement away from nice-weather places since they already have high relative house prices. With CES production and utility, the direction of movement depends on nontrivial parameter restrictions. As a rule of thumb, movement will be toward nice weather if the elasticity of substitution between non-housing goods and housing is below one (Rappaport 2004b). The intuition is similar to the exact balancing of income and substitution effects with log utility such that rising wages do not increase leisure consumption.

The final hypothesized way in which the contribution from weather to quality-of-life and productivity has changed is similar rising per capita income except that it applies only to the elderly. Social Security and better retirement planning have increased the wealth of retirees. Medical advances have increased their longevity. And many affluent individuals are increasingly deciding to retire early. Because they do not work, retirees' income no longer depends on their locale's productivity. And so upon retiring, quality-of-life suddenly becomes a much more important determinant of where they live.

The empirical section below argues that growth regressions can distinguish, at least in part, among these four possible changes in the weather's contribution to quality-of-life and productivity. Controlling for pre-determined agricultural, mineral extraction, and manufacturing characteristics of counties suggests that the movement towards nice weather does not arise primarily from a shift in industry composition. The faster relative growth of places with cooler, less humid summers establishes that air-conditioning can not alone account for the movement toward nice weather. And the approximately equal draw of nice weather for both working-age and elderly individuals suggests that increased retirement has has been a relatively unimportant source of the population shift. The explanation with which the empirics are most consistent is that individuals have been steadily increasing their valuation of nice weather's contribution to quality-of-life. Fitted growth rates suggest that air conditioning also played a large role in the population movement.

3 Econometric Framework

A locality's steady-state population density is assumed to depend on its productivity and quality-of-life. These, in turn, are assumed to depend on numerous time-invariant local attributes. More specifically, the natural log of steady-state population density for locality

i is assumed to take the functional form,

$$l^*_{i,t} = \rho_t l_t \; + \; \mathbf{x}_i' \boldsymbol{\beta}_t \; + \; \mu_{i,t} \qquad 0 \leq \rho < 1 \tag{1}$$

The term ρ is a time-varying scalar that captures any increasing returns from current population density to quality-of-life and productivity. The k-by-1 column vector $\mathbf{x}_i$ measures the locality's time-invariant attributes. These are multiplied by a time-varying k-by-1 column vector, $\boldsymbol{\beta}_t$. The stochastic disturbance, $\mu_{i,t}$, is assumed to have expectation zero and to be uncorrelated with $\mathbf{x}_i$.[4]

Of course, quality-of-life and productivity may also depend on time-varying, endogenous local attributes such as local government policy. To simplify the discussion that follows, any such contributions are assumed to occur only via current population, l_t. In practice, interpretations of regression coefficients need to consider the possibility that they reflect contributions from excluded time-varying attributes.

With imperfect factor mobility, regressing current density on time-invariant attributes is equivalent to estimating

$$\begin{aligned} l_{i,t} &= \left(\tfrac{1}{1-\rho_t}\right) \mathbf{x}_i' \boldsymbol{\beta}_t \; + \; \epsilon_{i,t} \\ \epsilon_{i,t} &= \left(\tfrac{1}{1-\rho_t}\right) \left(\left(l_{i,t} - l^*_{i,t} \right) + \; \mu_{i,t} \right) \end{aligned} \tag{2}$$

Regression coefficients on $\mathbf{x}_i$ thus correspond to the structural parameters, $\boldsymbol{\beta}_t$, magnified by the degree of increasing returns to scale. Such estimates will be biased. The error term, $\epsilon_{i,t}$, includes the difference between current and steady-state density. This difference will almost certainly be correlated with $\mathbf{x}_i$.

To get some intuition on the bias, it is helpful to assume that ρ_t equals zero. Further assume that up until $t = 0$, current density was at its steady state, $l_{i,t} = l^*_{i,-1} = \mathbf{x}_i' \boldsymbol{\beta}_{-1}$. Exactly at $t = 0$, steady-state density shifts to $l^*_{i,0} = \mathbf{x}_i' \boldsymbol{\beta}_0$, where it remains forever after. The difference between current and steady-state density immediately following the shift is $\mathbf{x}_i'(\boldsymbol{\beta}_{-1} - \boldsymbol{\beta}_0)$. A level regression based on (2) implemented at $t = 0$ would estimate $\boldsymbol{\beta}_{-1}$ rather than $\boldsymbol{\beta}_0$. Population density gradually transitions to its new steady state. As it does

[4]The label "steady state" might alternatively be reserved for a stronger condition characterized by substituting $l^{**}_{i,t}$ for both $l^*_{i,t}$ and $l_{i,t}$ in (1). Also, $\mathbf{x}_i$ is assumed to include a 1 as its first element thereby allowing for a time-varying constant.

so, regressions based on (2) will give coefficients that reflect a combination of the old and new structural parameters, $(1-\alpha_t)\boldsymbol{\beta}_{-1} + \alpha_t \boldsymbol{\beta}_0$, with α moving from 0 to 1 over time.

Reintroducing increasing returns to scale considerably complicates matters. Coefficients from level regressions based on (2) should still reflect a combination of old and new parameters. But even after the structural parameters, $\boldsymbol{\beta}_t$, change, the corresponding estimated coefficients can remain constant because of increasing returns to scale. Similarly, increases in ρ_t will cause an increase in the magnitude of estimated coefficients notwithstanding constant structural parameters, $\boldsymbol{\beta}_t$. For these reasons, regressions of population density on fixed attributes are difficult to interpret.

In contrast, regressions of the growth of population density on fixed attributes suggest more straightforward interpretations. Specifically, such coefficients should reflect the *direction* in which contributions to quality-of-life and productivity have shifted over time. The inclusion of initial density as a right-hand-side variable helps to control for increasing returns.

Interpreting population growth regressions requires making explicit the process by which population converges to its steady state.[5] It will be assumed to do so as a function of the log difference between steady-state and current density, $\lambda(l^*_{i,t} - l_{i,t})$, with $\lambda'(\,\cdot\,) > 0$ and $\lambda(\,0\,) = 0$. Local population growth is then given by

$$l_{i,t} - l_{i,t-1} \;=\; \lambda(\,l^*_{i,t-1} - l_{i,t-1}\,) \;+\; n_{i,t} \;+\; \nu_{i,t} \tag{3}$$

The term $n_{i,t}$ captures any change in population density due to births and deaths. The term $\nu_{i,t}$ is a stochastic shock with expectation zero. It is helpful to assume that both $n_{i,t}$ and $\nu_{i,t}$ are independent of $l^*_{i,t-1}$, $l_{i,t-1}$, and x_i.

The dependence of $\lambda(\,\cdot\,)$ on only the difference between steady-state and current density implies that this difference can be written as a function of three series—past changes in steady-state density, past births minus deaths, and past population growth shocks—along with the gap between steady-state and actual density at some time in the distant past:

$$l^*_{i,t-1} - l_{i,t-1} = f(\,\{l^*_{i,t-\tau} - l^*_{i,t-\tau-1}\}_{\tau=1}^{T-1}\,,\;\{n_{i,t-\tau}\}_{\tau=1}^{T}\,,\;\{\nu_{i,t-\tau}\}_{\tau=1}^{T}\,,\;l^*_{i,t-T} - l_{i,t-T}\,) \tag{4}$$

[5] So long as a place's land area remains constant, the growth rate of population density equals the growth rate of population. The two types of growth are referred to interchangeably herein.

The function $f(\,\cdot\,)$ has a positive partial derivative with respect to each element of its first series of arguments, a negative partial derivative with respect to each element of its second and third series of arguments, and a positive derivative with respect to the the last argument. Henceforth T is assumed to be large and so this last argument will be ignored.

Each of the past changes in steady-state density can be rewritten by first differencing (1). Doing so using an approximation of the change in the product of two time-varying variables gives

$$\begin{aligned} l^*_{i,t-\tau} - l^*_{i,t-\tau-1} \;\approx\; & \big(\rho_{t-\tau} - \rho_{t-\tau-1}\big)\, l_{i,t-\tau-1} \;+\; \mathbf{x}_i' \big(\boldsymbol{\beta}_{t-\tau} - \boldsymbol{\beta}_{t-\tau-1}\big) \\ & + \rho_{t-\tau-1}\,(l_{i,t-\tau} - l_{i,t-\tau-1}) \;+ \big(\mu_{i,t-\tau} - \mu_{i,t-\tau-1}\big) \end{aligned} \tag{5}$$

The change in steady-state population density is approximately the change in the degree of increasing returns multiplied by the initial population density plus the change in the contributions from the time-invariant attributes plus the change in population density multiplied by the initial degree of increasing returns plus the change in the stochastic disturbance.

Substituting (5) into (4) and the result into (3) and then rewriting in terms of a new function, $\widetilde{\lambda}(\,\cdot\,)$, gives

$$\begin{aligned} l_{i,t} - l_{i,t-1} \;=\; \widetilde{\lambda}\Big(& \{\big(\rho_{t-\tau} - \rho_{t-\tau-1}\big)\, l_{i,t-\tau-1}\}_{\tau=1}^{T-1} \;,\; \{\mathbf{x}_i' \big(\boldsymbol{\beta}_{t-\tau} - \boldsymbol{\beta}_{t-\tau-1}\big)\}_{\tau=1}^{T-1} \;, \\ & \{\rho_{t-\tau-1}\,(l_{i,t-\tau} - l_{i,t-\tau-1})\}_{\tau=1}^{T-1} \;,\; \{\mu_{i,t-\tau} - \mu_{i,t-\tau-1}\}_{\tau=1}^{T-1} \;, \\ & \{n_{i,t-\tau}\}_{\tau=1}^{T} \;,\; \{\nu_{i,t-\tau}\}_{\tau=1}^{T} \Big) \;+\; n_{i,t} \;+\; \nu_{i,t} \end{aligned} \tag{6}$$

The first derivative properties of $\lambda(\,\cdot\,)$ and $f(\,\cdot\,)$ imply that $\widetilde{\lambda}(\,\cdot\,)$ has positive partial derivatives with respect to each element of its first four series of arguments and negative partial derivatives with respect to each element of its fifth and sixth series of arguments.

The growth regressions that follow have reduced functional form,

$$l_{i,t} - l_{i,t-1} \;=\; a\, l_{i,t-1} \;+\; \mathbf{x}_i'\mathbf{b}_t \;+ \varepsilon_{i,t} \tag{7}$$

Comparing (7) with (6) shows that the coefficient a is an increasing function of each element of $\{(\rho_{t-\tau} - \rho_{t-\tau-1}) l_{i,t-\tau-1}/l_{i,t-1})\}_{\tau=1}^{T-1}$. In other words, the coefficient on initial density measures past changes in the degree of increasing returns to scale. Past increases in IRS contribute positively to a; past decreases contribute negatively to it. The term $l_{i,t-\tau-1}/l_{i,t-1}$

"adjusts" for the difference between current and lagged density. It should be close to one for recent periods. Similarly, each b_t^k of $\mathbf{b}_t$ is increasing with respect to each element of the series $\{(\beta_{t-\tau}^k - \beta_{t-\tau-1}^k)\}_{\tau=1}^{T-1}$. Positive past changes in the structural coefficient $\beta_{t-\tau}^k$ contribute positively to b_t^k; negative past changes contribute negatively to it. The intuition is straightforward: since population adjusts only gradually to its steady state, the partial correlation of growth with fixed attributes reflects the change over time of how those attributes contribute to steady-state density (Rappaport, 2004a).

The dependence of (6) on the series of past changes in population might suggest also including lagged growth terms on the right-hand-side of (7). But with the slow adjustment of population towards its steady-state, doing so will result in the corresponding autoregressive coefficients capturing a considerable share of the growth arising from past changes in the other structural coefficients. On the other hand, excluding lagged growth rates from regressions should simply magnify the positive correspondence between b_t^k and $\{(\beta_{t-\tau}^k - \beta_{t-\tau-1}^k)\}_{\tau=1}^{T-1}$ since the latter is a main source of the lagged growth.[6]

The present change interpretation of $\mathbf{b}_t$ differs substantially from a level interpretation that is sometimes made in the conditional convergence empirical literature. This alternative interpretation assumes a linear convergence process: $\lambda(\,\cdot\,) = -\lambda \cdot (l_{i,t-1} - l_{i,t-1}^*)$. The positive scalar λ measures a constant "speed of convergence"—the rate at which l closes the log gap to its steady state. Substituting this and (1) into (3) gives $l_{i,t} - l_{i,t-1} = -\lambda(1-\rho_{t-1})l_{i,t-1} + \lambda \mathbf{x}_i' \boldsymbol{\beta}_{t-1} + \lambda \mu_{i,t} + n_{i,t} + \nu_{i,t}$. The coefficient vector $\mathbf{b}_t$ can thus be interpreted as a positive scalar times the structural vector $\boldsymbol{\beta}_{t-1}$.

Two important problems strongly argue that level interpretations of $\mathbf{b}_t$ are incorrect. From a theoretical perspective, simple models of local growth show that the speed of convergence can vary tremendously even very close to the steady state (Rappaport, 2005). From an empirical perspective, the conditional convergence setup suggests that excluding initial population density should result in completely different coefficient estimates since in that case only the change interpretation applies. But as shown below, coefficient estimates are nearly identical whether or not initial population density is included.

[6]The exclusion of lagged growth does make it more difficult to interpret a to the extent that past growth is correlated with past population levels. Also, the exclusion of a control for past *natural* population change allows for the possibility that regression coefficients may partly be capturing it.

Regressions using county observations almost surely violate the classical assumption of independence. This is due to possible spatial components both of omitted variables and of stochastic disturbances. Hence a generalization of the Huber-White heteroskedastic-consistent estimator is used to report standard errors that are robust to a spatial structure among regression residuals (Conley, 1999). Let $\sigma_{i,j}$ be an element of the covariance matrix $E(\varepsilon\varepsilon')$. For observation pairs between which the Euclidean distance is beyond a certain cutoff, covariance between residuals is assumed to be zero. For observation pairs closer to each other than the cutoff, a declining weighting function is imposed to estimate residual covariance. Let $\mathrm{s}_{i,j}$ be the estimate of $\sigma_{i,j}$. And let e_i be a regression residual.

$$\mathrm{s}_{i,j} = g\left(\mathrm{distance}_{i,j}\right)\mathrm{e}_i\mathrm{e}_j \tag{8}$$

$$\begin{array}{ll} g\left(\mathrm{distance}_{i,j}\right) & \begin{cases} = 1 & : \quad \mathrm{distance}_{i,j} = 0 \\ \in [0,1] & : \quad 0 < \mathrm{distance}_{i,j} \leq \overline{d} \\ = 0 & : \quad \mathrm{distance}_{i,j} > \overline{d} \end{cases} \\ g'\left(\mathrm{distance}_{i,j}\right) & \leq 0 \end{array} \tag{9}$$

Herein, the weighting on the estimated covariance between residual terms is assumed to fall off quadratically as the distance between county centers increases to 200 kilometers.[7] Thus accounting for spatial correlation approximately doubles standard errors relative to the assumption of zero covariance with homoskedastic disturbances.

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

[7]In other words, $g(\cdot) = 1 - \left(\frac{\mathrm{distance}_{i,j}}{200}\right)^2$. Note that the present specification 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 $g(\cdot)$.

and can be considered exogenous relative to most data-generating processes.[8]

The primary dependent variable below is the annual growth rate of population density from 1970 to 2000. Other regressions use the growth rates of population subgroups, house prices, and income as their dependent variable. Summary statistics for the growth rates are included in Table 1. The variables are constructed from the various U.S. Census Bureau and Bureau of Economic Analysis sources listed in the bibliography.

The weather variables are derived from data purchased from The Climate Source, Inc. (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” is applied to such data to fit surfaces over a 2 km grid of the continental United States. A county’s weather values are then constructed as the mean over all 4 km^2 grid cells that lie within it. In the regressions, weather variables are entered with both a linear and quadratic term. The quadratic term has had the linear sample mean subtracted prior to squaring. Doing so allows the coefficient on the linear term to measure the marginal effect of an increase in the variable from the sample mean.

January daily maximum temperature is used as the measure of winter weather. It is the average maximum temperature for days in January; in other words, it is the average of the warmest temperature attained on each of the 930 January days from 1961 to 1990. The choice to use January daily maximum rather than minimum temperature reflects an a priori belief that winter daytime highs are likely to be a more important contributor to quality-of-life than winter nighttime lows. Results are extremely robust to using alternative winter temperature measures.

July daily maximum heat index and July average daily mean relative humidity are used as the dual measures of summer weather. The latter is the mean of average daily maximum and minimum humidity. The former is a discomfort index that combines average daily maximum temperature with average daily mean relative humidity (Stull, 2000). The inclusion of humidity entered independently in addition to its contribution to heat index is

[8]Nevertheless, a few adjustments to county geographies are required. Details are described in Rappaport and Sachs (2003).

motivated by its strong marginal power to account for population growth's sample variance. Results are extremely robust to using alternative summer temperature measures.

All regressions also include controls for precipitation. These are made up of linear and quadratic terms for average annual precipitation and for the average number of days per year on which there was at least 0.01 inches of precipitation. Maps depicting the distribution of each of the five weather elements across U.S. counties are included in the paper's supplemental materials.

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 ocean and Great Lakes shoreline per unit area. 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.

To control for increasing returns to scale, some of the growth regressions include an additional set of fourteen variables measuring initial population density and surrounding total population. 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 (the natural log of) total population of all counties with centers within 50 km from a county's own center. At a minimum, this innermost circle always includes the county's own population. A second ring measures the 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).

As discussed in the theory section, one of the explanations for the movement to nice weather is that it reflects the decline of agricultural, minerals extraction, and manufacturing employment. A set of seventeen variables, listed in Table 2, is used to control for this. The industry share variables are constructed from the 1970 decennial census. The remaining variables are constructed from data collected for the 1969 and 1972 economic censuses and disseminated in the U.S. Census Bureau Consolidated City and County Databook (ICPSR Study 7736).

5 Results

Throughout much of the 20th century, local population growth in the United States has been positively partially correlated with winter temperature and negatively partially correlated with summer temperature and summer humidity. Supporting results are presented and interpreted for three sets of regressions. The first takes 1970-to-2000 population growth as its dependent variable and incrementally introduces different categories of controls. The second set applies a base specification from the first set to several alternative dependent variable growth rates. The third set applies a base specification to decade growth rates from the 1880s through the 1990s. Together the results suggest that rising incomes are likely to have played a large role in causing the move to nice weather. They also suggest that air-conditioning was probably important as well.

5.1 Population Growth, 1970 to 2000

Results of the 1970-to-2000 growth regressions are reported in Table 3. In Column 1, the weather variables are included without any additional controls. A positive coefficient on January temperature statistically differs from zero at the 0.05 level. It implies that expected population growth increases as average daily maximum temperature increases above its sample mean value of 41°F. The positive, statistically-significant coefficient on quadratic January temperature implies that the higher expected population growth from warmer winter temperatures becomes larger as temperatures increase. This increasing quadratic relationship is intuitive if the advantage of warmer winter weather is the chance to participate in many outdoor recreational activities. Both July heat index and July relative humidity have negative, statistically-significant coefficients on their linear terms. Expected population growth falls as summer heat index and relative humidity increase from their respective sample means of

98°F and 66%.[9]

The signs and statistical significance of the coefficients on the winter and summer variables are extremely robust to introducing additional controls. Column 2 includes the coastal proximity and topography variables. Coastal proximity, which helps moderate extreme temperatures, is strongly positively correlated with population growth (Rappaport and Sachs, 2003). But controlling for coastal proximity only slightly tempers the coefficient values on the weather variables.

Column 3 additionally controls for initial density and for total surrounding population so as to capture any growth arising from increasing returns to scale. On the one hand, increasing returns may cause the partial correlation between population and a weather attribute to remain constant even after that attribute's contribution to quality-of-life and productivity has changed. On the other hand, changes in the degree of increasing returns may induce positive or negative partial correlations between population growth and an attribute notwithstanding unchanged contributions to quality-of-life and productivity. Directly controlling for the variables from which increasing returns derives should mitigate these problems. Doing so, the winter and summer coefficient magnitudes hardly change.

The close similarity of coefficients between the Column 2 and Column 3 regressions casts strong doubt on a conditional-convergence interpretation of the Column 3 coefficients. As discussed in the econometric section above, the regression of a variable's growth rate on its initial level potentially underpins a level structural interpretation of the coefficients on additional controls.[10] But no such interpretation is possible if the initial level of the dependent variable is excluded. Nearly identical results from including rather than excluding initial population density and initial total population can be interpreted in two ways. One is that the level structural parameters multiplied by the conditional convergence parameter are coincidentally identical to the change coefficients (that is, $\lambda\boldsymbol{\beta}_{t-1} = \boldsymbol{\beta}_{t-1} - \boldsymbol{\beta}_{t-2}$). The

[9]The negative partial correlation of population growth with summer temperature holds only when controlling for winter temperature. Otherwise, a positive coefficient on July heat index statistically differs from zero at the 0.05 level. This positive partial correlation of growth with July heat index when no control for winter temperature is included also holds for the specifications in the remaining columns of Table 3.

[10]The initial density spline included in the Column 3 regression is a generalization of initial population density entered linearly. The two are equivalent if the coefficients on the spline components are constrained to be equal.

more reasonable conclusion is that the conditional convergence specification fails.[11]

One of the explanations for the movement to nice weather is the historical decline of relative U.S. employment in the agricultural, mineral extraction, and heavy manufacturing industries. Column 4 reports results from a regression that includes controls for the initial concentration in each of these. The magnitude of the linear winter coefficient decreases moderately. More substantial decreases in the magnitude of the linear summer coefficients are partly offset by increases in the magnitude of the corresponding quadratic coefficients. And the winter and summer coefficients' pattern of statistical significance remains unchanged.[12]

It is important to note that the controls for initial industrial concentration likely absorb a larger share of variance than is actually caused by them. Remaining coefficients would then understate the weather's contribution to growth. Many industries require substantial investments that become immobile once they are made. Growing industries can more easily respond to individuals' shifting locational preferences since they tend to be investing at a high rate. As shown below, the move to nice weather began during the 1920s. Thereafter, contracting industries—such as agriculture, mineral extraction, and manufacturing—would become disproportionately concentrated in bad-weather places. A second reason why the industrial concentration variables likely absorb variance attributable to weather is that they may be correlated with excluded weather variables that are sources of growth (for example, the number of very cold and very hot days each year).

Overall, some portion of the move to nice weather probably does reflect the changing industrial composition of employment. But most of it probably does not.

Notwithstanding all the controls in the Column 4 regression, it is still possible that omitted variables might account for a portion of the partial correlations with winter and summer weather. But if so, the omitted variables are not region specific. The regression reported in Column 5 includes one-zero dummies for 8 of the 9 Census geographic divisions.

[11] A parallel criticism of structural interpretations of coefficients in cross-country growth regressions is that they reflect "good luck" rather than good long-term fundamentals (Easterly, Kremer, Pritchett, and Summers, 1993).

[12] Results are extremely similar if an expected wage growth variable is additionally included as a control. It is constructed as initial aggregate county labor income in each of 46 industry categories multiplied by the 1970-to-2000 national wage growth of each category (using the BEA REIS dataset). An analogous measure of expected employment growth is not constructed since only 11 industry categories are available to do so.

Coefficient values remain close to their values absent the division dummies. Coefficient values are similarly robust to the inclusion of dummies for each U.S. state (not shown).

Results are similarly robust to a weighted regression that considerably discounts low-population counties. The variance of the error term $\varepsilon_{i,t}$ in (7) may be larger for counties with low population. If so, ordinary-least-squares point estimates of parameters will not be efficient. The optimal GLS estimator involves pre-multiplying the left- and right-hand sides of (7) by the reciprocal square root of an observation's variance (Davidson and MacKinnon, 1993). Column 6 reports results from such a weighted regression using the same set of controls as in Column 4. The weighting premises that $\varepsilon_{i,t}$ is the sum of two stochastic components: one whose variance is independent of population and one whose variance is proportional to the reciprocal of population. It is assumed that for a county with population of one thousand, 75% of $\varepsilon_{i,t}$ derives from the population-dependent component.[13] This implies, for example, that for a county with one hundred residents, 97% of total variance derives from the population-dependent component. For a county with ten thousand residents, 23% of variance derives from it.

The coefficients in the weighted regression (Column 6) are quite similar to those in the unweighted one (Column 4). The main difference is that the negative coefficient on linear summer heat index differs from zero at the 0.10 rather than the 0.05 level. But the negative coefficient on quadratic summer temperature now differs from zero at the 0.05 level rather than not statistically differing from zero.[14]

The Column 4 unweighted regression will henceforth serve as a baseline. The implied magnitude of the winter weather coefficients is large. An increase in January temperature from one standard deviation below its sample mean to one standard deviation above its sample mean (from 29°F to 54°F) is associated with faster growth of 1.3% per year. Miami's Dade County, with an average January daily maximum temperature of 76°F, has faster expected annual growth of 3.4% per year compared to a county with mean winter temperature. For comparison, the mean population growth rate for U.S. counties from 1970 to 2000 was

[13]Specifically, $E\left(\varepsilon_i^2\right) = \sigma^2(1 + 3 \cdot \frac{1000}{population_i})$.

[14]Results are more fragile to a weighting that assumes $\varepsilon_{i,t}$ arises solely from a component with variance proportional to the reciprocal of population. The paper's supplemental materials include versions of Table 3 under several alternative weighting schemes.

0.9% per year with a standard deviation of 1.3%.

The implied magnitudes of the negative coefficients on summer weather in the baseline regression are also large, though slightly less so. An increase in July heat index from one standard deviation below its sample mean to one standard deviation above its sample mean (from 87°F to 109°F) is associated with slower growth of 0.5% per year. An increase in relative humidity from one standard deviation below its sample mean to one standard deviation above its sample mean (from 56% to 75%) is associated with slower growth of 0.9% per year.[15] Dade County's average July daily maximum heat index of 109°F and average July daily relative humidity of 74% imply annual growth 0.7% slower than a county with the sample mean values of summer heat index and humidity. Colorado's Summit County, home to many ski resorts, has a mean July heat index of 76°F and a mean relative humidity of 55%. As a result, it has faster expected annual growth of 0.6% compared to a county with summer weather equal to the sample mean.

In addition to the correlations with summer and winter weather, the regressions in Table 3 also find robust evidence of a negative quadratic partial correlation between population growth and precipitation days. The implied magnitude from the Column 4 baseline regression becomes large for places with an especially high number of rainy days. Because of the positive linear coefficient, increasing the number of rainy days by one standard deviation (25 days) above the mean (94 days) leaves expected population growth essentially unchanged. Increasing rainy days by a second and then a third standard deviation slows growth by 0.3 percentage points and then an additional 0.6 percentage points. For Seattle's King County, with an average 182 rainy days per year, annual expected population growth is 1.3 percentage points slower than a county with mean annual precipitation.

The five weather variables in Table 3—each entered linearly and quadratically—account for a very large share of the variance of population growth. The R-squared value from the regression with no controls is 0.272. For comparison, a regression of population growth on dummies for each U.S. state yields an R-squared value of 0.322. Additionally including the

[15]The reported slower growth from a higher heat index should be interpreted as arising solely from the temperature component. The reported slower growth from an increase in relative humidity includes the effect of the associated rise in heat index. In other words, it holds constant (at its sample mean) only the temperature component of heat index.

weather variables to the controls in the baseline Column 4 regression increases R-squared by 7.0 percentage points. Again for comparison, the marginal R-squared value from adding state dummies to the baseline controls is 12.4 percentage points.

Figure 2 shows the expected population growth attributable to weather as estimated by the baseline regression. In other words, it shows the vector product of the ten coefficients reported in Column 4 with counties' actual linear and quadratic weather values. The resulting expected growth captures the marginal effect of weather after controlling for coastal proximity, topography, initial density, initial surrounding population, and initial industrial composition. Expected growth from weather is highest in southern Florida, southwestern Texas, southern New Mexico, southern Arizona, southern California, and coastal northern California. Expected growth from weather is lowest throughout most of New England and the Midwest as well as in West Virginia and the Pacific Northwest.

The faster expected growth of places with cooler and less humid summers establishes that air-conditioning can not alone account for the move to nice weather. This point is nicely illustrated in Figure 2 by the high expected growth of California's coastal counties. These counties' mild summer weather implies that their rapid growth can not be attributable to air-conditioning. Conversely, if air-conditioning were the main force driving weather-related moves, then expected growth should be much higher throughout the deep South (which has among the most hot and humid weather in the U.S.).

Nevertheless, the pattern of expected growth suggests that air-conditioning was indeed important. The high expected population growth in southern Arizona and southern Florida holds despite average daily summer heat index values exceeding 110°F. This would almost certainly not be the case in the absence of air-conditioning.

5.2 Alternative Growth Rates

The movement to nice weather has not been primarily driven by any one group. Rather, growth's positive partial correlation with winter temperature and negative partial correlations with summer heat index and summer humidity hold for a number of sub-populations.

Table 4 Column 1 repeats the results from the baseline regression. Column 2 presents results for an analogous regression that uses firms' reported employment growth rather than population growth as its dependent variable. The magnitude of the negative coefficient on linear January temperature is moderately smaller than in the population growth regression, a difference that statistically differs from zero.[16] More important for present purposes is that the negative, statistically-significant coefficients on linear and quadratic January temperature imply a quantitatively-large negative partial correlation of employment growth with winter temperature. For summer heat and summer humidity, the implied magnitudes of the negative partial correlations are approximately equal across the two regressions.[17]

The more negative correlation with winter temperature of population growth than of employment growth is consistent with the retiree explanation of the move to nice weather. To the extent that retirees are indeed the major source of the migration, we might expect that the partial correlations with nice weather to be stronger for the elderly (aged 65 and up) than for working age individuals (aged 25 to 54). As shown in Columns 3 and 4, this is indeed the case both for the positive correlation with winter temperature and the negative correlation with summer heat index. The differences in coefficients between the two groups statistically differ from zero. Thus there is definitely some support for the retiree explanation. But as above, more important for present purposes is that the coefficients in the working-age regression remain statistically significant and large in magnitude. Elderly migration accounts for only part of the overall move to nice weather. Of course, it may be that elderly migration has served as a catalyst for migration by others, for instance by increasing labor demand in destination locales. But the early timing of the move to nice weather, discussed below, casts doubt on this latter possibility.

Another possible explanation for the move to nice weather is that it disproportionately reflects location choices by international immigrants rather than native-born U.S. citizens. The regressions reported in Columns 5 and 6 do find some support for this. The positive partial correlation with winter temperature is much stronger for immigrants than for natives. Similarly, the implied magnitude of the negative correlation with summer heat index is moderately larger for immigrants. Moreover, the weather variables account for a much higher

[16]The statistical significance is based on a regression that has population growth minus employment growth as its dependent variable. This regression and analogous ones for the remaining columns of Table 4 are reported in the paper's supplemental materials.

[17]Including the expected wage growth variable discussed in footnote 12, the coefficients on July humidity no longer statistically differ from zero.

share of the variation of immigrant growth than of native growth. Even so, growth's positive correlation with winter temperature and negative correlations with heat and humidity remain strong among native-born citizens.

Movement to nice weather caused by rising incomes suggests an analogous *intratemporal* result: high income individuals may disproportionately sort into high quality-of-life locales (Rappaport 2004b). Whether such sorting would increase or decrease over time is less clear. Data limitations force the use of education as a proxy for income. Columns 7 and 8 of Table 4 show results from regressing the growth rates of college graduates (i.e., with a bachelors degree) and non-graduates on the baseline specification. Both the positive partial correlation with winter temperature and the negative partial correlations with summer heat and humidity hold for both groups. But the magnitude of the positive correlation with winter temperature is larger for non-graduates. And higher R-squared values suggest that the weather is a relatively more important determinant of non-graduates' location decisions. Thus there is some evidence that the move to nice weather has been stronger for those with low income.

The static theory of compensating differentials suggests that a quality-of-life induced movement to nice weather should be accompanied by an increase in relative house prices and a decrease in relative wages. Hence the signs of the partial correlations between house price growth and weather ought to be the same as those for population growth. And the signs of the partial correlations for wage growth ought to be the opposite of those for population growth. In a dynamic framework, however, the relationship among population growth, house price growth, and wage growth is ambiguous. The ability of house prices and wages to jump discreetly but inability of population to do so causes nonmonotonic dynamics following an increase in quality-of-life (Rappaport 2004a).

Regressions of two measures of house price growth on the baseline specification are largely consistent with static theory. As shown in Table 5 Columns 1 and 2, the statistically-significant coefficients on linear January temperature and linear July heat index imply that at the respective sample means, house price growth increases as winters become warmer and decreases as summers become hotter. The opposite-signed quadratic coefficients imply that these relationships weaken as temperatures increase. But over observed sample values, the linear coefficients dominate the quadratic ones.

Regressions of two measures of wage growth on the baseline specification are less consistent with compensating-differential theory. As shown in Columns 3 and 4, a positive coefficient on linear winter temperature differs either at the 0.10 level (per worker labor income growth) or at the 0.05 level (per capita income growth). This is the opposite of what is needed to compensate for the increased desirability of warm winter weather. The positive correlation might reflect the second stage of a nonmonotonic extended transition. Or it might capture sorting by high income people into warmer winter places, notwithstanding the apparent greater draw of nice weather to non-college graduates.

In contrast to the positive correlation of wage growth with winter temperature, its positive correlation with July humidity is consistent with compensating-differential theory. Faster wage growth in more humid places is exactly what is required to compensate people for these places' decreased desirability. Moreover, the positive correlation reinforces that the decreased discomfort from heat and humidity afforded by air-conditioning has not been the primary driver of the move to nice weather. On the other hand, the positive correlation of wage growth with humidity might reflect that air-conditioning has decreased humidity's negative contribution to productivity rather than to quality-of-life.

5.3 Population Growth by Decade

The empirical results so far have been for growth rates from 1970 to 2000. But the movement to nice weather actually began in the 1920s. Such a dating reinforces the conclusion that it was in large part driven by the broad-based rise in incomes rather than one of the proposed alternative explanations.

Table 6 shows results from decade-by-decade population growth regressions. The specification is the same as in Table 3 Column 3 (the baseline specification excluding the industrial composition controls). Results are qualitatively similar if Census Division dummies are additionally included.

From the 1880s through the 1910s, people were actually moving to places with bad weather. During the first two decades, population growth was negatively correlated with winter temperature. During all four decades, population growth was positively correlated with summer temperature and humidity. Over this same period, agriculture's employment share was rapidly declining. Hence the shift away from agriculture need not imply movement towards nice weather.

Beginning with the 1920s regression, statistically-significant positive coefficients obtain on both linear and quadratic January temperature. And statistically-significant negative coefficients obtain on one or more of the summer heat and humidity terms. A first point is that manufacturing's employment share was approximately increasing through 1940 and then approximately constant through 1970. Since the movement towards nice weather persisted through both of these phases, the subsequent decline in manufacturing's employment share seems an unlikely cause. A second point is that the movement towards nice weather far predates the mass adoption of air-conditioning, which began in the late 1940s. AC's spread would thus seem to be too late to account for the population shift. Similarly, the increases in retiree longevity and financial security—also largely post World War 2 phenomena—occur too late to explain the early movement towards nice weather.

Still another explanation for the move to nice weather is that it captures the increasing ease with which people can do so. Railroads, the automobile, and the airplane have all helped make long-distance moves much less costly. Along with rapidly improving telecommunications technologies, they have also made it much easier to stay in touch with friends and families following long-distance moves. While such falling transportation costs almost certainly helped to facilitate the move to nice weather, the timing of the movement suggests that they were unlikely to be the main cause. Railroads were a relatively mature technology many decades before the onset of the move to nice weather. Conversely, it was probably not until the construction of the interstate highway system in the 1950s that the automobile yielded significant time savings on long-distance journeys. Widely affordable air travel arrived even later.

6 Conclusions

Throughout most of the 20th century, U.S. residents migrated to places with nice weather. Possible explanations for this include the introduction of air-conditioning, the shift in the industrial composition of U.S. employment, increased elderly migration, and the broad-based rise in people's income. Regressions of 1970-to-2000 population growth on weather suggest that each of these explanations played a role. The positive partial correlations of population growth with summer heat and humidity establish that air-conditioning cannot alone account for the migration. But the high expected growth attributable to weather in places characterized by extreme summer heat and humidity almost certainly would not be the case in the absence of air-conditioning. An extensive set of controls for initial industrial structure accounts for a portion of the weather related moves. But the draw of nice weather remains strong nevertheless. And the move to nice weather has indeed been larger for the elderly, but only moderately so. That the movement to nice weather began in the 1920s reaffirms that it can not be explained by some combination of air-conditioning, shifting industrial structure, and increased elderly migration.

The inability of the alternative explanations to account for a large portion of the move to nice weather is consistent with an increasing valuation of the weather's contribution to quality-of-life having served as an important impetus. An increased valuation has been documented in the compensating differential literature and is theoretically predicted from the sharp rise in people's incomes over the course of the 20th century. With sufficient complementarity among non-housing goods, housing, and nice weather, the increased valuation of the latter requires migration toward it.

The present set of results suggest several lines of future research. One is the extent to which migration to nice weather has occurred or can be expected to occur in nations and regions other than the United States. Large increases in income have been experienced throughout the industrialized world. Many other places are currently experiencing such income growth or hope to do so in the near future. Of course, the degree of labor mobility in many places is likely to be well below that of the U.S. Some initial research along this line finds migration among Japanese prefectures over the period 1955 to 1990 to be negatively correlated with a measure of extreme temperature (Barro and Sala-i-Martin, 1995). Similarly, population growth from 1980 to 2000 *within* EU countries is indeed higher where weather is nicer. But *across* EU nations, population growth is uncorrelated with weather (Cheshire and Magrini, 2005). If European integration continues over time, the lure of better weather may eventually pull people across national borders as well.

A second line of research is the extent to which the U.S. migration to nice weather can be expected to continue. The introduction of air-conditioning represents a discrete shock.

The transition to the implied new steady-state population distribution might take several decades. But it would eventually die out. In contrast, the U.S. population is rapidly aging. And broad-based technological progress and the associated increase in per capita income are likely to endure. Hence the movement to nice weather is likely to do so as well.

A third line of research is the extent to which the draw of nice weather has been paralleled by a movement to places with high levels of other consumption amenities. Coasts, mountains, lakes, and national parks offer numerous recreational opportunities. So do urban amenities such as restaurants, museums, live performance venues, and professional sports. Other likely draws include low pollution; low traffic; and high-quality schools, universities, and hospitals. It may be that such quality-of-life amenities rather than targeted tax breaks and low wages are the key to future local economic development.

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Table 1: Summary Statistics

Variable	Obs	Mean	Std. Dev	Min	Max
1970-to-2000 Growth Rates					
Population	3,067	0.9	1.3	-2.4	10.1
Employment (Civilian)	3,065	1.8	1.5	-2.8	11.3
Working Age Pop. (aged 25 to 54)	3,067	1.7	1.4	-2.4	11.3
Elderly Population (aged 65 and up)	3,066	1.7	1.4	-2.2	10.0
Native U.S. citizen	3,067	0.8	1.3	-2.5	10.0
Immigrant	3,067	3.5	4.3	-8.3	24.4
Per Worker Labor Income	3,065	0.5	0.8	-15.1	5.8
Per Capita Income (1969 to 1999)	3,067	2.2	0.5	-0.6	4.8
Median House Value	3,063	2.3	0.9	-3.7	7.7
Median House Rent	3,049	1.4	0.7	-1.2	4.2
Population Growth Rates by Decade					
1880s	2,395	3.5	7.0	-13.2	69.2
1890s	2,604	1.9	3.2	-11.5	37.9
1900s	2,696	2.0	4.1	-8.8	45.6
1910s	2,844	0.7	2.2	-21.9	30.9
1920s	3,014	0.7	2.8	-8.9	44.3
1930s	3,060	0.5	1.5	-6.4	15.0
1940s	3,062	0.3	2.0	-9.3	14.5
1950s	3,064	0.4	2.2	-5.5	15.7
1960s	3,063	0.4	1.7	-11.3	12.1
1970s	3,067	1.4	1.7	-4.5	13.0
1980s	3,067	0.3	1.4	-3.9	9.7
1990s	3,069	1.0	1.3	-4.7	10.7
Weather					
January Daily Max. Temp. (°F)	3,067	41.4	12.4	10.8	76.5
July Daily Heat Index (°F)	3,067	98.3	11.1	75.6	131.3
July Daily Relative Humidity	3,067	65.7	9.6	23.8	82.0
Annual Precipitation	3,067	38.3	14.1	3.5	118.2
Annual Precipitation Days	3,067	94.1	24.5	13.3	198.0

All growth rates are on an annual percentage basis.

Table 2: Agriculture, Manufacturing, and Mineral Extraction Control Variables

Industry Share of 1970 Total Employment (10)	Additional Controls
Agriculture	**Additional Agriculture Controls (3)**
Mining	Farming Occupation Share (1969)
Primary Metals Manufacturing	Percent of Land Devoted to Farming (1969)
Fabricated Metals Manufacturing	Agriculture Sales per Capita (1969)
Machinery Manufacturing	**Additional Manufacturing Controls (2)**
Transportation Equip. Manufacturing	Manufact. Industries Payroll per Capita (1972)
Other Durable Manufacturing	Manufact. Industries Val. Added per Capita (1972)
Textiles Manufacturing	**Additional Mineral Controls (2)**
Chemicals Manufacturing	Mineral Industries Payroll per Capita (1972)
Other Nondurable Manufacturing	Mineral Industries Sales per Capita (1972)

Table 3: Population Growth and Weather

		(1)	(2)	(3)	(4)	(5)	(6)
Dependent Vairable →				**annual population growth rate, 1970 to 2000**			
Independent Variables ↓							
Coast/River/Topgrphy (7)		**no**	**yes**	**yes**	**yes**	**yes**	**yes**
Initial Density Spline (7)		**no**	**no**	**yes**	**yes**	**yes**	**yes**
Concentric Total Pop (7)		**no**	**no**	**yes**	**yes**	**yes**	**yes**
Ag/Mnrl/Mnfct (17)		**no**	**no**	**no**	**yes**	**yes**	**yes**
Census Divisions (8)		**no**	**no**	**no**	**no**	**yes**	**no**
Weighted Regression		**no**	**no**	**no**	**no**	**no**	**yes**
January Daily Max Temp	linear	***0.0751***	***0.0663***	***0.0655***	***0.0513***	***0.0497***	***0.0488***
		(0.0073)	***(0.0079)***	***(0.0074)***	***(0.0070)***	***(0.0077)***	***(0.0070)***
	quadratic	***0.0012***	***0.0012***	***0.0014***	***0.0013***	***0.0016***	***0.0013***
		(0.0003)	***(0.0003)***	***(0.0003)***	***(0.0003)***	***(0.0003)***	***(0.0002)***
July Daily Heat Index	linear	***-0.0626***	***-0.0508***	***-0.0505***	***-0.0215***	***-0.0242***	*-0.0170*
		(0.0091)	***(0.0102)***	***(0.0100)***	***(0.0088)***	***(0.0091)***	*(0.0088)*
	quadratic	-0.0002	-0.0003	0.0004	-0.0006	-0.0002	***-0.0008***
		(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	***(0.0004)***
July Daily Rel Humidity	linear	***-0.0371***	***-0.0410***	***-0.0621***	***-0.0395***	***-0.0549***	***-0.0385***
		(0.0110)	***(0.0114)***	***(0.0124)***	***(0.0103)***	***(0.0106)***	***(0.0099)***
	quadratic	0.0005	0.0006	-0.0001	-0.0003	***-0.0008***	-0.0003
		(0.0004)	(0.0004)	(0.0003)	(0.0003)	***(0.0003)***	(0.0003)
Annual Precipitation	linear	***0.0216***	***0.0231***	*0.0153*	-0.0044	-0.0029	-0.0048
		(0.0081)	***(0.0082)***	*(0.0078)*	(0.0066)	(0.0075)	(0.0064)
	quadratic	***-0.0004***	***-0.0004***	0.0001	*0.0002*	0.0002	*0.0002*
		(0.0002)	***(0.0002)***	(0.0002)	*(0.0001)*	(0.0001)	*(0.0001)*
Annual Precipitation Days	linear	0.0053	0.0041	0.0021	0.0064	0.0061	*0.0065*
		(0.0047)	(0.0048)	(0.0048)	(0.0039)	(0.0045)	*(0.0038)*
	quadratic	***-0.0002***	***-0.0002***	***-0.0003***	***-0.0002***	***-0.0002***	***-0.0002***
		(0.0001)	***(0.0001)***	***(0.0001)***	***(0.0000)***	***(0.0000)***	***(0.0000)***
Observations		3,067	3,067	3,067	3,067	3,067	3,067
# of Indep. Variables		10	17	31	48	56	48
R-sqrd		0.272	0.282	0.382	0.503	0.517	0.497
Control Variables R-sqrd			0.094	0.226	0.433	0.471	0.423
Marginal R-sqrd			0.188	0.156	0.070	0.046	0.074

Table shows results from regressing ([log(2000 Pop Density)-log(1970 Pop Density)]×100/30) 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 a spatial correlation using the procedure discussed in the main text. Bold type signifies coefficients that statistically differ from zero at the 0.05 level. Italic type signifies coefficients that statistically different from zero at the 0.10 level. The column 6 regression weights observations according to 1/(1+3000/population).

Table 4: Population Subgroup Growth and Weather

Dependent Vairable → Independent Variables ↓		(1) Total Population Growth	(2) Employ-ment Growth	(3) Elderly Population Growth	(4) Working Age Pop. Growth	(5) Immigrant Population Growth	(6) Native U.S. Citizen Pop. Growth	(7) College Graduate Pop. Growth	(8) College Non-Graduate Pop. Growth
Precipitation (4)		yes	yes	yes	yes	yes	yes	yes	yes
Coast/River/Topography (7)		yes	yes	yes	yes	yes	yes	yes	yes
Initial Density Spline* (7)		yes	yes	yes	yes	yes	yes	yes	yes
Concentric Total Pop* (7)		yes	yes	yes	yes	yes	yes	yes	yes
Ag/Mnrl/Mnfct (17)		yes	yes	yes	yes	yes	yes	yes	yes
January Daily Max Temp	linear	**0.0513**	**0.0354**	**0.0607**	**0.0529**	**0.2010**	**0.0439**	**0.0376**	**0.0529**
		(0.0070)	**(0.0074)**	**(0.0070)**	**(0.0073)**	**(0.0184)**	**(0.0071)**	**(0.0094)**	**(0.0068)**
	quadratic	**0.0013**	**0.0012**	**0.0016**	**0.0012**	-0.0002	**0.0012**	**0.0014**	**0.0013**
		(0.0003)	**(0.0003)**	**(0.0003)**	**(0.0003)**	(0.0007)	**(0.0003)**	**(0.0003)**	**(0.0002)**
July Daily Heat Index	linear	**-0.0215**	**-0.0248**	**-0.0340**	**-0.0217**	-0.0294	*-0.0171*	**-0.0253**	**-0.0172**
		(0.0088)	**(0.0093)**	**(0.0097)**	**(0.0091)**	(0.0247)	*(0.0088)*	**(0.0123)**	**(0.0086)**
	quadratic	-0.0006	*-0.0007*	**-0.0013**	-0.0002	**-0.0022**	-0.0005	*-0.0009*	**-0.0008**
		(0.0004)	*(0.0004)*	**(0.0004)**	(0.0004)	**(0.0010)**	(0.0004)	*(0.0005)*	**(0.0004)**
July Daily Rel Humidity	linear	**-0.0395**	**-0.0238**	**-0.0224**	**-0.0301**	-0.0499	**-0.0370**	*-0.0252*	**-0.0378**
		(0.0103)	**(0.0115)**	**(0.0102)**	**(0.0109)**	(0.0309)	**(0.0102)**	*(0.0131)*	**(0.0102)**
	quadratic	-0.0003	**-0.0008**	-0.0003	-0.0004	-0.0001	-0.0003	**-0.0013**	0.0000
		(0.0003)	**(0.0004)**	(0.0003)	(0.0003)	(0.0008)	(0.0003)	**(0.0004)**	(0.0003)
Observations		3,067	3,065	3,066	3,067	3,067	3,067	3,066	3,067
Number of Indep. Variables		48	48	48	48	48	48	48	48
R-squared		0.503	0.475	0.531	0.507	0.424	0.496	0.327	0.509
Non-Weather Control Variables R-squared		0.433	0.445	0.454	0.441	0.284	0.437	0.287	0.419
Marginal R-squared		0.070	0.030	0.077	0.066	0.141	0.059	0.040	0.090

Table shows results from regressing annual percentage growth rates for the listed population subgroups on the column 4 specification in Table 3. Quadratic weather variables have had their respective sample mean subtracted. Standard errors in parentheses are robust to a spatial correlation using the procedure discussed in the main text. Bold type signifies coefficients that statistically differ from zero at the 0.05 level. Italic type signifies coefficients that statistically different from zero at the 0.10 level. For the column 2 regression, the initial density spline and surrounding total controls are constructed using employment rather than population. For the regressions in columns 3 and 4, working age is defined to be from 25 to 54; elderly, 65 and above.

Table 5: Wage and House Price Growth and Weather

Dependent Vairable → Independent Variables ↓		(1) Median House Value Growth	(2) Median House Rent Growth	(3) Per Worker Labor Income Growth	(4) Per Capita Income Growth
Precipitation (4)		**yes**	**yes**	**yes**	**yes**
Coast/River/Topography (7)		**yes**	**yes**	**yes**	**yes**
Initial Density Spline (7)		**yes**	**yes**	**yes**	**yes**
Concentric Total Pop (7)		**yes**	**yes**	**yes**	**yes**
Ag/Mnrl/Mnfct (17)		**yes**	**yes**	**yes**	**yes**
January Daily Max Temp	linear	***0.0298***	***0.0353***	*0.0068*	***0.0087***
		(0.0051)	***(0.0029)***	*(0.0036)*	***(0.0028)***
	quadratic	***-0.0004***	***-0.0003***	0.0002	-0.0001
		(0.0002)	***(0.0001)***	(0.0002)	(0.0001)
July Daily Heat Index	linear	***-0.0353***	***-0.0125***	-0.0041	-0.0049
		(0.0067)	***(0.0035)***	(0.0043)	(0.0033)
	quadratic	0.0002	***0.0007***	***0.0007***	*0.0002*
		(0.0003)	***(0.0001)***	***(0.0001)***	*(0.0001)*
July Daily Rel Humidity	linear	0.0055	0.0008	***0.0149***	***0.0289***
		(0.0070)	(0.0045)	***(0.0053)***	***(0.0039)***
	quadratic	-0.0002	-0.0001	***0.0007***	0.0001
		(0.0002)	(0.0001)	***(0.0002)***	(0.0001)
Observations		3,063	3,049	3,065	3,067
Number of Indep. Variables		48	48	48	48
R-squared		0.404	0.533	0.322	0.386
Non-Weather Control Variables R-squared		0.287	0.287	0.369	0.362
Marginal R-squared		0.117	0.247	-0.048	0.024

Table shows results from regressing annual percentage growth rates for the listed wage and house price measures on the column 4 specification in Table 3. Quadratic weather variables have had their respective sample mean subtracted. Standard errors in parentheses are robust to a spatial correlation using the procedure discussed in the main text. Bold type signifies coefficients that statistically differ from zero at the 0.05 level. Italic type signifies coefficients that statistically different from zero at the 0.10 level. For the column 3 regression, the initial density spline and surrounding total controls are constructed using employment rather than population.

Table 6: Population Growth and Weather by Decade

Δlog(PopDensity)→ Indpndnt Variables ↓		(1) 1880 –1890	(2) 1890 –1900	(3) 1900 –1910	(4) 1910 –1920	(5) 1920 –1930	(6) 1930 –1940	(7) 1940 –1950	(8) 1950 –1960	(9) 1960 –1970	(10) 1970 –1980	(11) 1980 –1990	(12) 1990 –2000
Precipitation		yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Coast/River/Topography		yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Initial Density Spline		yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Concentric Total Pop		yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
January Daily Max Temp	linear	***-0.2061***	***-0.0788***	-0.0322	-0.0056	***0.0698***	***0.0515***	***0.0748***	***0.0682***	***0.0357***	***0.0779***	***0.0579***	***0.0534***
		(0.0387)	***(0.0200)***	(0.0211)	(0.0158)	***(0.0179)***	***(0.0091)***	***(0.0100)***	***(0.0110)***	***(0.0081)***	***(0.0092)***	***(0.0078)***	***(0.0078)***
	quadratic	-0.0020	***0.0042***	-0.0001	0.0001	***0.0029***	***0.0014***	***0.0017***	***0.0036***	***0.0020***	***0.0015***	***0.0021***	0.0004
		(0.0013)	***(0.0010)***	(0.0008)	(0.0007)	***(0.0008)***	***(0.0004)***	***(0.0003)***	***(0.0005)***	***(0.0004)***	***(0.0004)***	***(0.0003)***	(0.0003)
July Daily Max Heat Index	linear	***0.2756***	***0.0593***	***0.1299***	***0.0431***	-0.0168	***-0.0703***	***-0.0590***	***-0.0531***	***-0.0447***	***-0.0561***	***-0.0520***	***-0.0410***
		(0.0526)	***(0.0231)***	***(0.0274)***	***(0.0209)***	(0.0214)	***(0.0116)***	***(0.0135)***	***(0.0135)***	***(0.0104)***	***(0.0125)***	***(0.0109)***	***(0.0106)***
	quadratic	***-0.0075***	***-0.0020***	***-0.0034***	***-0.0018***	***-0.0027***	-0.0001	***-0.0026***	***-0.0026***	-0.0003	0.0005	0.0000	***0.0010***
		(0.0018)	***(0.0010)***	***(0.0011)***	***(0.0007)***	***(0.0009)***	(0.0005)	***(0.0005)***	***(0.0005)***	(0.0005)	(0.0005)	(0.0004)	***(0.0004)***
July Daily Rel Humidity	linear	***0.1301***	***0.0750***	***0.0663***	***0.0474***	0.0082	0.0158	***-0.0313***	***-0.0908***	***-0.0833***	***-0.0781***	***-0.0666***	***-0.0391***
		(0.0477)	***(0.0289)***	***(0.0331)***	***(0.0213)***	(0.0256)	(0.0133)	***(0.0146)***	***(0.0167)***	***(0.0142)***	***(0.0155)***	***(0.0131)***	***(0.0128)***
	quadratic	***-0.0071***	0.0007	***-0.0022***	0.0002	***-0.0031***	***0.0009***	-0.0001	***-0.0015***	*-0.0009*	-0.0004	-0.0003	0.0002
		(0.0013)	(0.0008)	***(0.0010)***	(0.0007)	***(0.0010)***	***(0.0004)***	(0.0005)	***(0.0006)***	*(0.0005)*	(0.0004)	(0.0004)	(0.0004)
Observations		2,395	2,604	2,696	2,844	3,014	3,060	3,062	3,064	3,063	3,067	3,067	3,069
Independent Variables		31	31	31	31	31	31	31	31	31	31	31	31
R-squared		0.735	0.406	0.591	0.122	0.325	0.192	0.368	0.411	0.316	0.311	0.399	0.317
Non-Weather Control Variables R-squared		0.664	0.294	0.537	0.104	0.208	0.108	0.283	0.335	0.265	0.183	0.260	0.190
Marginal R-squared		0.071	0.112	0.054	0.018	0.118	0.084	0.085	0.076	0.051	0.128	0.138	0.127

Table shows results from regressing annual percentage population growth rates for the listed decade on the column 3 specification in Table 3. Quadratic weather variables have had their respective sample mean subtracted. Standard errors in parentheses are robust to a spatial correlation using the procedure discussed in the main text. Bold type signifies coefficients that statistically differ from zero at the 0.05 level. Italic type signifies coefficients that statistically different from zero at the 0.10 level.

Figure 1: Iso-Utility over Weather

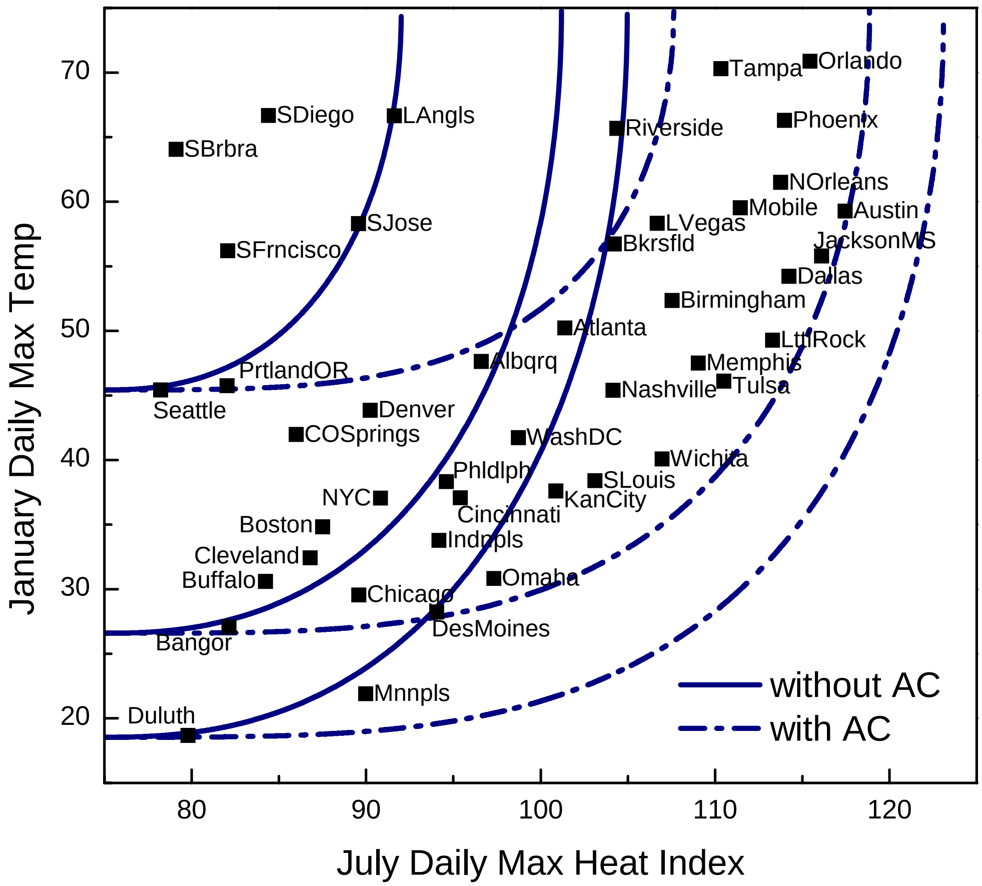

Figure 2: Expected Population Growth from Weather, (1970-2000)

Fitted annual pop. growth rate, controlling for coast, topography, initial density, concentric pop., and industry

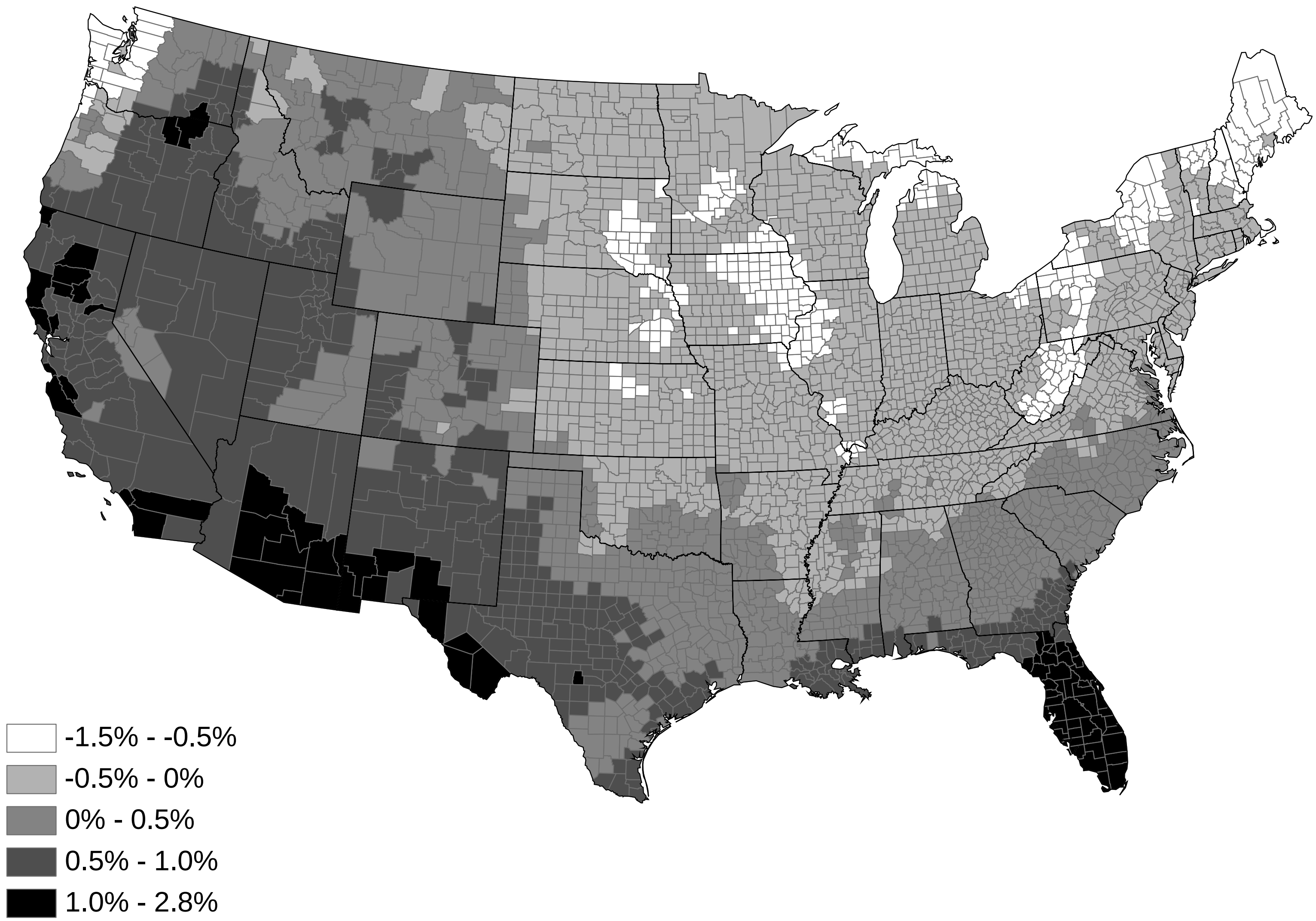

Figure 2: Expected Population Growth from Weather, (1970-2000)

Fitted annual pop. growth rate, controlling for coast, topography, initial density, concentric pop., and industry