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by

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ABSTRACT

Spatial heterogeneity is introduced as an explanation for local-area growth mechanisms, especially employment growth. As these effects are difficult to detect using conventional regression approaches, we use Geographically Weighted Regressions (GWR) for non-metropolitan U.S. counties. We test for geographic heterogeneity in the growth parameters and compare them to global regression estimates. The results indicate significant heterogeneity in the regression coefficients across the country, most notably for amenities and college graduate shares. Using GWR also exposes significant local variations that are masked by global estimates suggesting limitations of a one-size fits all approach to describe growth and to inform public policy.

I. INTRODUCTION

The longstanding decline in agricultural employment (Barkley 1990) has led to heightened interest in other potential sources of rural employment growth, especially in traditionally agriculture-dependent areas. Researchers have turned their attention to a host of both standard and novel prescriptions such as household amenities, human capital, new economy firms, and fiscal policy (Deller et al. 2001; Goetz and Rupasingha 2002; Huang et al. 2002; McGranahan 2002; Thompson et al. 2006). Yet, despite recognition of potential rural-urban differences (Ferguson et al. forthcoming), an unexplored aspect of this research is the degree of spatial heterogeneity (nonstationarity) in rural U.S. growth dynamics. Spatial heterogeneity may be expected to arise because local labor markets vary in their structure, social context, and histories (Lloyd and Shuttleworth 2005) in ways not readily captured by standard explanatory variables in global regressions. To paraphrase the old expression, "if you have seen one rural community, you have seen only one rural community."

Spatial heterogeneity in growth dynamics could render global estimates misleading in terms of local outcomes. For example, accepted findings with respect to the role of key variables in economic growth may be the result of global estimates (e.g., ordinary least squares, OLS) that mask significant local variation, even in the direction of influence. Alternatively, the standard estimates may suggest no marginal effect, while in reality the factor stimulates growth in some areas while reducing it in others, yielding an average effect of about zero. Aside from the importance of discovering the true nature of the relationships, successful local economic development policy requires knowledge of local socioeconomic processes and growth dynamics (Blank 2005; Nizalov and Loveridge 2005).[1]

A recent approach gaining popularity in accounting for potential geographic heterogeneity in socioeconomic processes is the geographically weighted regression (GWR) (Fotheringham et al. 2002). In contrast to the global regression approach, GWR can estimate separate coefficients, potentially for each observation (area). In estimating each region's *own* regression, characteristics of the individual areas included in the sub-sample are weighted by their spatial proximity. Spatial weighting smoothes variation in parameter estimates, revealing broad regional differences in the local marginal responses. Although still relatively uncommon, GWR is increasingly being applied in regional analysis. Recent applications include examinations of geographic heterogeneity in regional socioeconomic processes related to poverty (Benson et al. 2005; Farrow et al. 2005), commuting (Lloyd and Shuttleworth 2005), regional industrialization (Huang and Leung 2002), regional growth effects of agricultural policy in Western Europe (Bivand and Brunstad 2003), and local employment growth in Canada (Shearmur et al. 2006).

In terms of potential spatial heterogeneity in rural growth dynamics, Deller et al. (2001) raise the possibility that there may be agglomerative or interactive growth effects of amenities. Spatial differences in such effects could produce heterogeneity in rural growth responses, and potentially differences in appropriate policies. For example, in contrast to U.S. results, Ferguson et al. (forthcoming) find that amenities have relatively little influence on Canadian migration relative to economic factors, especially in rural Canada. Huang et al. (2002) discuss how human capital effects on growth are likely to vary regionally, possibly producing a "brain drain" in some regions. Though one could imagine using carefully selected interaction variables to detect these spatial variations with global approaches, this would require intricate knowledge of the specific set of interactions and adequate degrees of freedom, while specification problems such as multicollinearity could be exacerbated.[2]

In addition to the value of the GWR approach in terms of revealing spatial heterogeneity, the results can also inform global approaches. Region-specific results may provide a more detailed perspective on underlying relationships, allowing refinements in the global specification. Indeed, severe misspecification bias has been found in general spatial interaction modeling because of the spatial variation in local parameters, which could be missed in global approaches (Fotheringham 1984; 1986).

Therefore, this paper empirically assesses the spatial heterogeneity of nonmetropolitan county employment growth dynamics over 1990-2004. In particular, we hypothesize that there is significant spatial variation in the influence of climate/natural amenity and human capital on employment growth. We compare global regression estimates with the variation in GWR estimates for growth-related factors. Among the findings of particular interest, statistically significant geographic variation in employment growth responses is found for amenities, college completion, and immigration. Interestingly, the influence of agriculture's employment share on subsequent job growth does not vary spatially across the country.

Some amenity variables are found to have insignificant global effects, suggesting little marginal impact in traditional analysis. Yet, the GWR approach reveals a rich pattern, showing that these variables may have locally statistically significant effects that (nationally) offset one another. Likewise, greater college attainment stimulates growth in some areas, while reducing it in others. Immigration effects also vary from negative to positive. Generally, we conclude that "one size does *not* fit all" in understanding the underlying growth processes and in informing local economic development policymaking. Moreover, we believe our findings can help refine global specifications and that the geographical diversity of results can stimulate new hypotheses concerning rural growth processes. In particular, one question that arises is why the influences change so suddenly over geographic space—producing knife edges—even within what are thought to be relatively homogenous regions?

In the next section, we develop a model of nonmetropolitan employment growth, including a discussion of how heterogeneity in growth processes can arise. Section III follows with the empirical implementation of the model. Section IV presents and compares global regression results with those of GWR, including maps illustrating the geographic variation in employment growth responses to key variables. The final section summarizes the results and discusses their implications for rural economic development policymaking and for regional/urban modeling, including ways to improve global methods.

II. THEORETICAL FRAMEWORK

Our theoretical framework builds on the Roback (1982) static general equilibrium formulation of household and firm location. We follow Partridge and Rickman (2006) and Partridge et al. (2007; forthcoming) in adapting the Roback model to an employment growth framework. Because the Roback framework is well-known, we sketch only the important details. A novel feature of our approach is allowing underlying firm and household location dynamics to vary geographically, which can produce heterogeneous growth dynamics. We also show how supposedly competing hypotheses can actually be "correct," it is just that their respective validity applies to selective regions and locations.

Firm Location

Firms choose their location i to maximize profits (Π_i), the difference between total revenues and costs associated with production at that site. Costs depend on the nominal wage rate (w_i), the rental rate of land, and delivered costs of intermediate inputs. Revenues are influenced by product price and productivity, in which location-specific attributes can cause the *Π* function to vary across locations.

Human capital is a common component of growth models and regularly forms a pillar of economic development strategies targeting the emerging knowledge economy. However, Huang et al. (2002) observe that in some rural areas, increased human capital may reduce growth (also see the overview in Artz (2003)). They argue that while increasing human capital through education raises a household's income in rural areas, it may have a greater impact in urban areas, causing a rural "brain drain." Moreover, this may vary according to broad geographic differences in amenities and industry structure because college educated households and skill-based firms may especially prefer amenity-rich areas. In this case, there will be push and pull forces that induce more-educated households to move towards areas endowed with relatively more amenities, pulling down the entire low-amenity region. Thus, in "challenged" areas with a weak industry mix and/or poor amenities, it is possible that a higher *initial* college educated population share would be inversely associated with *subsequent* local job growth, while the more "standard" positive association would prevail in other areas. This type of spatial heterogeneity is precisely the type of relationship that GWR is intended to uncover.

Although we focus primarily on rural areas where small scale implies that agglomeration economies are not directly a key factor, proximity within the urban hierarchy is still a determinant of rural firm location (Polèse 2005; Polèse and Shearmur 2004). Core urban centers are associated with agglomeration economies (production externalities), which decay with distance, resulting in a distance growth penalty for rural areas (Hanson 1997). This occurs especially if offsetting urban congestion effects are small. There are also reasons to suspect potential spatial heterogeneity in agglomeration effects on rural areas. For example, the rural distance penalty to reach the nearest urban centers may be smaller in densely populated regions because there are alternative access points to agglomeration economies. Likewise, there may be geographic differences in the composition of product cycle stages of rural industries, in which mature industries are more likely to disperse (e.g., relocation to rural greenfields). Features such as coastal locations, topography, or infrastructure also would likely contribute to the spatial heterogeneity.

Together with geographic position in the urban hierarchy represented by distance of rural area i to the j most proximate urban tiers in the hierarchy ($DIST_{ij}$), we assume the differences in delivered costs of intermediate inputs and land rents mostly relate to own-area population density (*N*). Other profit variations arise from differentials in wages (*w*) and human capital (K^H), which then yield the following indirect profit function:

$$\Pi_i = F_i(w_i, DIST_{ij}, K^H_i, N_i) \qquad [1]$$

Based on the above discussion, we expect the profit relationships Π_i to vary geographically. We assume that labor demand is a function of firm profitability and that firms move to (move away from) regions with rates of profit above (below) the national average rate of return. Thus, a region with an above average rate of return will have increases in labor demand over time (Partridge and Rickman 2003).

Household Location

Households are assumed to migrate in response to location-specific utility differentials. Utility is assumed to depend positively on the wage rate and the amenity attractiveness of the area, and negatively on land costs (Roback 1982). The location's amenity attractiveness depends on both a fixed level of natural amenity stocks (S_i) and an endogenously determined component related to population density.

Even though most natural amenities are relatively stable over time, their geographical valuation by households can differ across regions, inducing differential effects on migration. Graves and Mueser (1993) argue that household valuation of amenities may vary spatially with average income differences (amenities are usually normal goods). Spatial variations could also be the result of household life-cycle considerations, to the extent that regions have different age distributions. Moreover, household preferences for amenities are likely heterogeneous (Johnston et al. 2003). For example, those who choose to live in "Northern lake districts" may prefer cool summers and winter recreation opportunities, while those who choose to live in Florida may prefer warm winters. Agglomerative or interactive effects among amenities (Deller et al. 2001) may further result in geographic variation in the marginal growth effects of individual amenities. For example, the effects of climate on migration may depend on whether one is considering relocating to an urban area or a rural community with differing access to particular recreation opportunities.

Access to urban areas also can enhance household amenity attractiveness of a rural area as urban areas support more retail, cultural, and recreational venues (Glaeser 1997; Krugman 1993). Alternatively, higher crimes, taxes, land prices, traffic congestion, and environmental pollution, associated with city size thresholds may cause households to move out of the cities (Glaeser 1997). However, there may be heterogeneity in rural growth effects of spatial proximity to urban areas because some of these factors are difficult, at best, to measure accurately; preferences for these amenities/disamenities may vary geographically; and unmeasured heterogeneity in other factors such as local public infrastructure may exist. Finally, population density positively affects the price of housing through land scarcity in a given region, such that households whose preference is to consume more housing may move to the hinterland in search of lower housing costs. Heterogeneity in this effect may occur because of geographic differences in zoning regulations and local public infrastructure.

More formally, distance of location *i* to the nearest urban center affects both commuting access to jobs and access to urban services and related amenities. The role of distance depends on the size or tier-level of the urban center, as well as distances to even higher-level cities that offer a greater range of work opportunities, higher wages, and higher-order urban amenities ($DIST_{ij}$). Thus, we can write indirect household utility as:

$$V_i = G_i(w_i, DIST_{ij}, N_i, S_i, \cdot) \qquad [2]$$

in which based on the above discussion we expect that the utility relationships V vary across i. Following equation [2], we assume that labor supply is related to household utility and that households will relocate to (move away from) regions with above (below) the national average level of utility. Hence, we assume that labor supply will be increasing (decreasing) in regions with an above (a below) average rate of utility (Partridge and Rickman 2003).

Reduced Form Employment Growth Equation

Following the discussion surrounding equations [1] and [2], the change in labor demand and the change and in labor supply can be obtained from those equations (Partridge and Rickman 2003; Partridge et al. 2007). Setting the change in labor demand equal to the change in labor supply by substituting out wages, a reduced-form expression for employment growth in region *i* ($EmpGr_i$) can be derived as:

$$EmpGr_i = H_i\,(DIST_{ij}, N_i, S_i, K^H{}_{i}, \cdot) \qquad [3]$$

We hypothesize that underlying heterogeneity in firm and household location processes will cause employment growth responses H_i to vary across regions.

III. EMPIRICAL MODEL

The dependent variable in the regression models is the county-level percentage change in total employment for the 1990 to 2004 period. The employment data are compiled by the U.S. Bureau of Economic Analysis (BEA) and made available at the Regional Economic Information System (REIS) website. Only counties in the contiguous U.S., including the District of Columbia (D.C.), are examined.

The 2003 metropolitan area (MA) boundaries from the U.S. Census Bureau are used to divide the sample into nonmetropolitan (1,972 counties) and metropolitan (1,057) counties.[3] Sensitivity analysis is conducted using earlier MA definitions. We assume that the nonmetro and metro data generating processes are sufficiently different that pooling the samples in any way would bias the nonmetro results.[4]

Geographically Weighted Regression (GWR) Specification

GWR accounts for spatial heterogeneity in responses to variables by estimating separate regressions for each sample observation including the location of interest and other spatially-weighted observations (Fotheringham et al. 2002). The weights represent the adjacency effects for neighboring locations within a specified distance (or bandwidth). Following the assumption that more proximate locations are more alike, the weights decay with distance following a bi-square decay function for an adaptive kernel.[5] When regression points and observation points are the same, one regression is estimated for each observation, allowing parameter estimates to vary across the sample space.

To illustrate, a GWR model intended to estimate one regression for each observation is specified as:

$$y_i = \beta_{i0} + \beta_{i1}x_{i1} + \beta_{i2}x_{i2} + \cdots + \beta_{ik}x_{ik} + \varepsilon_i \, ; \; \varepsilon_i \sim N(0, \sigma^2), \; i = 1, 2, \ldots, n \qquad [4]$$

where the i subscripts on the parameters indicate that there is a separate set of $(k+1)$ parameters for each of the n observations (n=number of counties in our case). The GWR parameter estimates are provided by:

$$\hat{\beta}_i = (X'W_iX)^{-1}X'W_iY \, ; \; i = 1, 2, \ldots, n \qquad [5]$$

where $\boldsymbol{W}_i$ is the n x n weight matrix whose off-diagonal elements are zero and the diagonal elements are the weights of each observation relative to i, i.e., $\boldsymbol{W}_i = diag(w_{i1}, w_{i2}, \ldots, w_{in})$.

The optimal bandwidth distance or the optimal number of neighboring units used in each observation's regression is determined by the "cross-validation score" or Akaike Information Criterion (AIC) tests. Following suggestions in Fotheringham et al. (2002), we use an adaptive kernel which is more suitable for a study area that is characterized by non-uniform distribution of sample units (sparse distribution of counties in the northwestern part and dense distribution in the eastern part of the U.S.). The optimal bandwidth in this analysis is presented in terms of the number of nearest neighbors (as opposed to an alternative of using a fixed distance). Based on the AIC test criterion, the optimal number of nearest neighbors n* was found to be 846 and 893 for the nonmetro and metro samples respectively. This means that the nearest 846 nonmetropolitan counties will be used in the estimation of each nonmetropolitan county's GWR regression, with the county's nearest neighbors receiving a much greater weight.

The GWR approach has key advantages over standard approaches. One advantage is that since each county has its own constant term, it somewhat accounts for county fixed effects. Also, because we control for many explanatory variables, one possible shortcoming is multicollinearity, which can be problematic in standard approaches such as OLS as well as in individual local GWR regressions. Yet, because the GWR approach produces literally thousands of regressions, examining the median and the entire range of estimates should balance any outlier estimates. That is, because multicollinearity implies that the regression estimates are unbiased but measured with less precision, considering a large range of estimates allows us to "average" the estimates, better determining their central tendencies and distribution.

Another advantage the GWR approach has over global OLS techniques is that it can greatly reduce spatial error correlation when there is (county) heterogeneity in the GWR coefficients, and the β_{ij}'s and the $\boldsymbol{X}$ variables are spatially correlated (Fotheringham et al. 2002). Conversely, because standard approaches estimate one fixed global set of regression coefficients, spatially clustered groups of counties could have residuals that are either over- or underestimated. In standard approaches, the ensuing spatial correlation caused by the underlying heterogeneity in the regression coefficients would be indistinguishable from standard spatial error correlation that is generated by shocks originating in one county impacting others. Yet, by definition, GWR approaches directly correct for the spatial heterogeneity of the regression coefficients that are the root cause of this problem. A disadvantage of GWR is that because the local regressions often use a sample size that is smaller than the total sample size, the resulting coefficients may be less efficiently estimated than those from global approaches.

Explanatory Factors

Generally, our empirical approach follows those found in the literature, in which numerous variables are included to reduce the possibility of omitted variable bias (e.g., see the discussion of Partridge et al. 2007). To mitigate endogeneity problems, the explanatory variables are generally measured in 1990, though our natural amenity variables are exogenous by definition (further details of variable construction and descriptive statistics are in Appendix Table 1). Although the expected effects of many of our variables are apparent (while others are included simply as control variables), some predicted effects of key variables are described below.

County *i*'s local GWR specification corresponding to its sample bandwidth can be denoted as:[6]

$$\%\Delta \mathrm{Emp}_{i(t\text{-}0)} = \alpha_i + \delta_i\, \mathrm{POPDEN}_{i0} + \boldsymbol{\gamma}_i \mathbf{AMENITY}_{i0} + \theta_i\, \mathbf{DEMOG}_{i0} + \boldsymbol{\psi}_i \mathbf{ECON}_{i0} + \boldsymbol{\varphi}_i\, \mathbf{DIST}_{\mathbf{ij}} + \varepsilon_{i(t\text{-}0)} \qquad [6]$$

$i = 1, 2, 3\ldots n$, where $n = 1{,}972$ in the rural/nonmetro sample and $n = 1{,}057$ in the MA sample.

POPDEN$_i$ is the initial-period population density, which is included to control for own-county agglomeration or congestion effects. $\mathbf{AMENITY}_i$, $\mathbf{DEMOG}_i$, $\mathbf{ECON}_i$, and $\mathbf{DIST}_{\mathbf{ij}}$ are vectors that respectively represent amenities, demographic attributes, economic characteristics, and geographic attributes such as distance to different tiers in the urban hierarchy. The regression coefficients corresponding to each sample point *i* are α_i, δ_i, $\boldsymbol{\gamma}_i$, $\boldsymbol{\theta}_i$, $\boldsymbol{\psi}_i$, $\boldsymbol{\varphi}_i$; and ε_i is the residual.

The effects of climate and natural amenities (i.e., $\mathbf{AMENITY}_i$) are proxied by: three climate variables (January temperature, January sunshine hours, and July humidity); percent water area of each county; and a 1 to 24 county typography measure that is positively related to hilly and mountainous terrain. We generally expect favorable natural amenities to be positively related to growth primarily because it attracts new migrants, which in turn attracts employers—i.e., jobs follow the people.

As discussed in the theoretical section, the influence of the amenity variables is expected to spatially vary across the country (i.e., differing $\boldsymbol{\gamma}_i$). For example, lakes and water-cover may have entirely different *marginal impacts* in the interior of the country than near the coasts. We also hypothesize that a higher average January temperature will have different impacts in far northern versus Sunbelt locations. And to the extent that an amenity negatively affects productivity (possibly hills and mountains), it may offset the positive household attractiveness and reduce growth. Likewise, we also expect stronger favorable impacts from higher January temperatures in urban areas where transportation can be greatly affected by inclement weather and where the offsetting amenities effects from outdoor winter recreation may be smaller because these activities are more difficult to access (e.g., snowmobiling).

To account for demographic and human capital effects (**DEMOG**$_i$), we include 1990 population shares of four education categories, the percent of the population that immigrated between 1985 and 1990, six 1990 population age shares, and five race and ethnicity population shares. Regarding the education variables, most of our focus will be on the impact of the population share of those 25 years and older with at least a four-year college degree to assess our hypothesis about the potential offsetting effects of greater human capital for growth versus brain drain through out-migration. Human capital effects in growth models suggest counties with greater college graduate shares will have experience faster job growth (Simon 1998; Simon and Nardinelli 2002; Glaeser and Shapiro 2003). This is reinforced if there are positive local productivity spillovers from having greater employment shares of more educated workers (Moretti 2004). Yet, human capital models of migration suggest that college graduates are the most geographically mobile, in part due to responsiveness to demand shocks. Further, if natural amenities are normal or superior goods, then college graduates may be especially predisposed to migrate away from low-amenity areas to high amenity areas, which can confound the "knowledge-economy" patterns just described. A regional industry composition that is facing restructuring would be an additional "push" factor. The result would be spatial variation in the influence of the college graduate share variable.

To account for initial economic conditions and any corresponding disequilibrium migration, in **ECON**$_i$, we control for the initial unemployment rate (1990), median household income (1989), goods-producing and agriculture shares (1990). To control for differences in labor demand and economic strength, the industry mix employment growth rate over the 1990-2000 period is also included. A county's industry mix employment growth rate is what would be expected if the county's industries grew at their corresponding national rates over the 1990-2000 period (see Appendix Table 1).[7] Thus, the industry mix growth rate reflects whether the county has a favorable industry mix (in terms of job growth) and is a commonly used exogenous measure of labor demand because national industry growth rates are used in its calculation. To account for economic spillovers in the neighboring *economic region*, the corresponding unemployment rate, median household income, and industry mix employment growth in the surrounding counties within the U.S. Bureau of Economic Analysis (BEA) region are included.[8] Thus, our model accounts for regional economic spillovers as well as differential local labor demand shifts.

To assess the role of distance and proximity in the urban hierarchy, we include five metrics of a county's distance from its nearest urban center, as well as from successively higher-tiered urban centers ($\mathbf{DIST_{ij}}$). First, we measure distance from the population weighted centroid of the county to the population weighted centroid of the *nearest* urban center (a micropolitan area or an MA).[9] For a county that is part of an urban center, the nearest urban center distance is calculated as the distance to the population weighted centroid of its *own* MA or micropolitan area (zero for a one-county MA or micropolitan area).

The second distance variable represents the incremental or additional distance to the nearest MA. Obviously, this distance would be zero for counties inside a metro area. The third distance variable represents the incremental distance to a MA of over 250,000 people. The fourth and fifth distance variables represent the incremental distance to a MA of over 500,000 and 1.5 million people respectively. These incremental distances capture potentially successively larger distance penalties to reach metro centers with higher-order business and household services and amenities (Partridge et al. 2007; forthcoming). Alternatively, distance protection from spatial competition may lead to more job growth as suggested in some New Economic Geography models (Fujita et al. 1999). Together with differences in infrastructure, we expect that the influence of urban proximity is also subject to spatial variation.

IV. EMPIRICAL RESULTS

The results for nonmetropolitan counties are presented in Table 1; for comparison and validation purposes, metropolitan county results appear in Table 2. Consistent with our primary hypotheses, we stress the spatial differences in the marginal effects of key natural amenity attributes and the human capital variables because of their importance for both academic and policy purposes. Asterisks next to the variable names indicate statistical significance of spatial variation across the country in the GWR coefficients, as determined by the Monte Carlo test described in Fotheringham et al. (2002) and Charlton et al. (2003).[10] The global ordinary least squares (OLS) estimates and global estimates from maximum likelihood (ML) estimation of the spatial error model (SEM) specification (Anselin 1988) are also presented in Tables 1 and 2. These global models are shown for comparison to assess whether they discard important spatial variation and to show how GWR findings can be used to improve standard global specifications (Bivand and Brunstad 2003). The SEM model assumes that for more proximate counties, there is cross-sectional correlation in the regression residuals.[11] For both the OLS and SEM specifications, cross (†) signs indicate parameter significance.

Base Results for Nonmetropolitan Counties

Our general hypothesis of significant spatial variation in the regression coefficients is supported. The F-statistic at the bottom of Table 1 reveals that the GWR specification is a statistically significant improvement over the OLS model, which is further indicated by its higher adjusted-R^2 value. The spatial autocorrelation coefficient (reported at the bottom of the table in the SEM column) is statistically significant. Nevertheless, there are few tangible differences when comparing the SEM results to either the OLS or the median GWR estimates, suggesting the spatial autocorrelation is more of the nuisance variety than one that alters our basic conclusions.

From the first three and last two columns of Table 1, we see that the GWR coefficients for 27 of 37 variables in the nonmetro sample exhibit significant spatial heterogeneity. This includes all variable groups except the age-distribution variables. Global approaches such as OLS and SEM mask this heterogeneity which, for two critical reasons, could produce potentially misleading findings. First, the implications of this heterogeneity would be lost in policy advice—i.e., one-size policies do not fit all. Second, global approaches may suggest a variable is insignificant, when in fact it has a statistically significant (though offsetting) impact for large parts of the sample.

Turning to our more specific hypotheses regarding the individual variables, all three climate variables exhibit significant spatial variation, though reflective of the discussion above, only the average January temperature is statistically significant in the OLS and SEM specifications. A warmer winter (a higher average January temperature) is positively associated with faster job growth for the “typical” nonmetro county, though the GWR estimated coefficients range from a minimum of -0.915 to a maximum of 0.976. For average sun hours in January, and July humidity, though the median impacts are near zero, there are both negative and positive GWR estimated coefficients which are statistically significantly different from one another. It is not surprising then that the OLS and SEM global estimates for their coefficients are insignificant, which would lead one to incorrectly conclude that these variables have no economically meaningful impacts.

To illustrate the spatial variation in the effects of the average January temperature variable, the GWR coefficients are mapped. Figure 1 shows that the expected positive warm winter-employment growth relationship is most dominant in the Northeast and the Southeast—cold Northeastern winters are associated with much less job growth and warm Southeastern winters with much faster job growth. Yet, concluding that household migration is solely towards warm winters could be misleading. In the Northwest and especially the Upper Midwest, January temperature is inversely related to job growth, consistent with winter outdoor recreation activities supporting stronger growth. Migration may occur because of tourism jobs related to winter sports or because of the amenity attractiveness of winter sports themselves for household location. In fact, the average January temperature is lower in counties classified as recreation counties (by Economic Research Services of the U.S. Department of Agriculture) compared to other counties in Michigan, Minnesota, and Wisconsin. The differences between recreation and other counties for Minnesota and Michigan were statistically significant below the 10% level based on a difference of means (assuming equal variances) t-test, while the p-value for Wisconsin was 0.13.[12]

Another notable natural amenity is access to water and lakes, which is proxied by the percent of land area covered by water. Not surprisingly, this variable's OLS and SEM regression coefficients are positive and statistically significant. Yet, again indicative of spatial heterogeneity, the GWR coefficients are significantly different across the sample space with both positive and negative estimated effects. Illustrating this spatial diversity, Figure 2 maps the estimated percent-water-area regression coefficients. Access to water has its strongest positive impacts in the Great Plains, consistent with water being a key amenity in attracting households. There are also favorable employment effects in most of the West and in western Kentucky and Tennessee. However, accessibility to water has small marginal impacts on job growth in most of the rural Eastern U.S. and Texas. With a couple of exceptions, one likely reason for this pattern is scarcity—areas with the least access to water areas assign it a higher marginal value.

Hills and mountains are another natural amenity that is valued by many households. Using the U.S. Department of Agriculture (USDA) typography measure as a proxy, the expected response is reflected by the positive and significant OLS and SEM coefficients. Though most of the estimated coefficients are positive like the global estimates, there is a statistically significant difference in the GWR coefficients across the sample. Figure 3 maps the GWR typography coefficients. Again, we observe an east-west dichotomy with hills and mountains having small effects in eastern counties, while more rugged western counties demonstrate more favorable employment impacts. One possible explanation is the more forested landscape in the east represents transportation barriers and a lack of open, flat, space to locate economic activity, serving as a disamenity. Contrarily, hills and mountains in the West, where there is more open space, represent clearer vistas and increased recreational opportunities, acting as a positive amenity. Nevertheless, the strongest positive effects are in the south central region, showing how the local terrain can have favorable amenity effects in attracting businesses and people (e.g., the Ozarks). Overall then, variations in the influence of natural amenities across the country suggest that while they can be an asset to revitalize many rural communities, communities need to tailor their efforts to their particular amenity assets. Adopting "success stories" of other communities may prove to be unsuccessful or even counterproductive.

Regarding the human capital (education) variables, only greater shares of the population with some college and with four-year college degrees have strong positive effects on the typical nonmetro county's job growth. This is reflected by the positive and significant SEM and OLS coefficients and the positive median GWR coefficients, supporting various human capital and knowledge spillover hypotheses. Yet, assuming a universally positive effect appears to be overly simplistic as reflected in Figure 4's mapping of the college graduate GWR coefficients.

The human capital effect results for the West are very different from those for the East. Greater college graduate shares are associated with faster employment growth in the West, but the positive effect declines when moving east, with negative effects appearing in the Northeast. These results are consistent with our hypotheses described in Sections II and III. The strong positive college graduate effects in the West are consistent with human capital migration effects as well as amenities attracting new workers—with the most educated being more mobile on average. At first glance, the negative coefficients in the East are somewhat surprising. However, if high natural amenities are attracting college graduates to some areas of the West, they have to be coming from somewhere, and one possible origin is the East. In fact, the correlation between the GWR coefficients for the college graduate share and the amenity scale is 0.45, supporting the amenity-based interpretation. To be sure, the result of interacting the college graduate share with the amenity scale in the OLS regression suggests that the college graduate share effect is significantly greater for amenity-rich areas (not shown).[13]

Likewise, given greater propensities to migrate (Yankow 2003), a greater share of the college educated can accelerate the rate of decline in a region suffering adverse demand shocks. This implies that eastern rural areas experiencing declines in labor demand and are at risk of brain drains. Policies to enhance human capital in these regions may be ineffective or even counterproductive unless the underlying factors that induce the out-migration of college graduates are mitigated. This may be even more challenging if the reason more jobs are being created in the West is that industries requiring college education are attracted to high natural amenities in the West. Yet, we found that the correlation between the amenity index and the change in the college graduate share of the population during the 1990s is near zero (not shown), suggesting that amenities attract households of all skill levels, and it is not an amenity effect on skill-based industries—i.e., jobs follow people.

Regarding international immigration, the median GWR, OLS, and SEM models all suggest that having a greater 1990 population share that immigrated between 1985 and 1990 is positively associated with subsequent population growth in nonmetropolitan counties. The regression coefficients being greater than one suggest favorable multiplier effects. For example, higher initial shares of immigrants may have positive multiplier effects if they attract more immigrants (e.g., chained migration) or represent a source of increased local demand. The GWR results also reveal significant spatial variation, though almost all counties have a positive immigrant-population growth linkage.

Only in the upper Midwest, there are negative immigration effect values (not shown). Immigration's effect in western areas is moderately positive while it is moderate to large in counties in the south central and northeastern regions. Negative or small positive effects would occur if immigrants depress local wages, triggering out-migration of native-born residents, or depress growth through lower human capital. A few pockets in Arkansas, Indiana, Michigan, Ohio and northern Pennsylvania are associated with especially large immigrant multiplier effects. Perhaps immigrants are predisposed to take certain jobs in these regions (say food processing) that displace few native residents. For example, some of these regions possess areas in decline, which can provide vacated low-skilled jobs and cheap housing for immigrants (Glaeser and Gyourko 2005). These wide-ranging results may help explain the diverse opinions surrounding the immigration debate, and indicate how immigration policies may also need to be informed by knowledge of heterogeneity in spatial effects.

Regarding the growth effects of distance, the median values of all the GWR incremental urban distance variables are negative. This is also the case for the OLS and SEM estimates, in which these coefficients are statistically significant (with one exception). The magnitudes of the coefficients indicate that the penalty is strongest for the distance to the nearest urban center with the marginal impact of the distance penalty tending to decrease when considering incremental distances to higher-level tiers in the urban hierarchy. These results imply that rural county job growth is dependent on proximity to an urban center, even as small as 10,000 people, confirming that remoteness is a major deterrent to job growth for most counties outside a metro area (Partridge et al. 2006). In addition, the first four distance variable coefficients exhibit statistically significant spatial variation across the sample. Regarding the distance to the nearest urban center, the coefficients at the upper quartile and lower quartile range from -0.072 to -0.142.

Interestingly, one variable whose effects do not vary spatially across the country is the initial agricultural employment share, despite considerable heterogeneity in practices. In fact, the global OLS and SEM estimates also suggest that agricultural intensity has little long-term effect on subsequent employment growth. This implies that proximity to the urban center could underlie past findings that farming intensity is inversely associated with rural growth. For example, when removing the distance variables from the GWR model, the spatial variation in the agricultural share coefficients became statistically significant at the 5% level (not shown). Nevertheless, when the distance variables were omitted from the OLS and SEM specifications, the agricultural employment share remained insignificant (though negative), suggesting that global regression specifications have difficulty capturing the instances where the agricultural employment share has been important for growth. Yet, it is also likely that agriculture's (negative) influence has waned as its share of the rural economy has declined.

Comparison to Metropolitan County Results

Table 2 provides a summary of the MA county results. Again, the GWR specification shows marked improvement in parameter estimates and goodness-of-fit over OLS. As before, the SEM specification yields parameter estimates similar to those from OLS, though spatial autocorrelation in the residuals is virtually absent. Only 20 (as opposed to 27 in the nonmetro sample) out of 36 variables show significant spatial variation across the sample space. As illustrated below, the differences point to the importance of separately considering nonmetropolitan and metropolitan counties.

All three climate variable coefficients have the expected signs and are highly statistically significant in the global OLS and SEM regressions (though the GWR median average January sun hours coefficient is negative). The three climate GWR coefficients also vary significantly across the sample, supporting our hypothesis of spatial heterogeneity. Average January temperature has a positive influence on MA job growth that is generally stronger than in the nonmetro case (i.e., the GWR MA distribution of average January temperature coefficients is positioned to the right of that for nonmetro areas).

Figure 5 shows the spatial distribution of the average January temperature GWR coefficients. As for the nonmetro sample, marginal effects are greater in the East than the West. The strongest positive growth effects of warmer January temperatures appear in the Southeast, while colder January temperatures have a strong adverse effect in the Northeast. In contrast to the nonmetro results, colder January temperatures inhibit growth in upper Midwest MAs, likely through snow and cold limiting some types of productive activities, without providing the growth benefits of winter tourism.

In contrast to the nonmetro results, access to water has very little influence on MA job growth, *ceteris paribus,* where if anything, the OLS, SEM, and median GWR estimates all suggest a negative association (though insignificant). Also in contrast to the nonmetro results, the OLS and SEM typography coefficients are statistically insignificant. Yet, this also obscures statistically significant spatial variation in the GWR results shown in Figure 6. Consistent with the nonmetro patterns, typography has greater positive influence in southcentral and western counties, with small marginal impacts in the East, suggesting a common explanation for the heterogeneity in both the nonmetro and metro estimates.

The standard regression approaches suggest that educational attainment has relatively little impact on 1990-2004 MA job growth (at least in a statistical sense). Surprisingly, even the initial share of college graduates is insignificant in the standard approaches, which is in contrast to the rather strong effects detected in past studies for American cities (e.g., Simon 1998; Simon and Nardinelli 2002; Glaeser and Shapiro 2003). Yet, we caution that our specification and sample differs from past research. Among the education variables, only the GWR college graduate coefficients significantly vary across the country.

Figure 7 maps the GWR college graduate results. The MA pattern is very similar to the east-west nonmetro pattern identified above. As with the nonmetro results, amenity-driven migration may produce a brain drain effect from the East (*ceteris paribus*). This contrasts with the global regression results which suggested the initial college graduate share has little or no influence, obscuring the rich spatial diversity across the nation. The similarity in pattern applying across the nonmetro and metro samples indicates that it is not simply a statistical anomaly in one sample.

Unlike the positive effects of immigrant population on nonmetro job growth, its influence on MA job growth appears to be mixed. Both the OLS and the SEM specifications yield negative though insignificant coefficients. The GWR specification yields positive median and upper quartile coefficient estimates but negative lower quartile values. The general pattern is that greater initial immigrant shares are associated with faster job growth in East Coast MAs, but the effect turns sharply negative when moving west (not shown). Much of the West is more accessible to immigration from Mexico, which may be associated with different growth dynamics. Alternatively, or in combination, native (and long-term immigrant) residents in western MAs may be more likely to out-migrate in response to new immigrants (i.e., an offsetting labor supply response). Consistent with the nonmetropolitan results, immigrants may be locating in areas where natives were moving out for other reasons (e.g., frostbelt-sunbelt migration), leaving vacant jobs and durable housing.

Sensitivity Analysis

Two sets of sensitivity analyses were conducted to assess the robustness of the results. First, we re-estimated the models employing 1999 MA boundary definitions. This results in fewer MA counties (824) and more nonmetro counties (2,205). Using the 1999 boundaries means that the MA area boundaries that existed as result of the 1990 Census would be unchanged, but any newly designated MA counties during the 1990s would be included in the nonmetropolitan sample. For the most part, this definition of nonmetropolitan counties excludes some MAs that were established after 1999 and it excludes counties that were added to the individual MAs as a result of the 2000 Census.[14] Although there are some differences, none of the general conclusions would be affected by using this sample.

Another possible concern is that the 1990s experience could be described as a robust economic period dominated by growth of the knowledge economy. Yet, the early part of the current decade was highlighted by 9-11 and the associated economic slowdown, suggesting that the economic structure may have changed. Thus, the second set of sensitivity analysis uses 1990-2000 employment growth as the dependent variable rather than 1990-2004 to assess any differences (using 2003 boundaries). If there was no structural change in the economy, then the magnitude of the base 1990-2004 model coefficients should be uniformly larger than the 1990-2000 coefficients because there would be more years of job growth to explain (i.e., the dependent variable is larger on average). If there was a structural change, then there would be no uniform pattern that applies to all variables. These results suggest that there is no clear structural change, especially for nonmetro areas.[15]

V. SUMMARY AND CONCLUSIONS

Following the past literature, we derived a model that predicts spatial heterogeneity in the marginal impacts of particular variables. We also contend that various competing theories regarding the influence of certain variables may all be "correct," but their predictive capacity depends on the specific location being considered. Confirming our hypotheses, using the GWR approach, we found spatial heterogeneity in nonmetropolitan county employment growth dynamics over the 1990 to 2004 period for most of the explanatory variables. Of particular interest, we found significant spatial variation in the growth effects of natural amenities and human capital, consistent with those hypotheses. For some amenity variables, global regression estimates suggested there was no "average" effect on growth, while the GWR estimates indicated positive effects in some regions and negative effects in other regions. Curiously, the influence of the initial period agricultural employment share did not (statistically) vary geographically. Heterogeneity in growth effects of other variables such as immigration and typography also was explored.

The revealed spatial heterogeneity can inform local policymaking by indicating how much growth, or lack of growth, may be attributed to the region's specific amenities. For example, although a higher average January temperature is positively associated with faster employment growth for the "typical" nonmetropolitan county, for some counties it reduces growth, perhaps through limiting winter recreational activities in counties dependent on them. Our findings also suggest that it would be fruitful to develop water-based recreation in the rural Plains region, while for regions where water is more plentiful, such efforts are less likely to pay off. College attainment among the population was found to more likely spur growth in the West, than in the East, where a "brain drain" may be the outcome.

By helping detect important interactions, the analysis also spawned the opportunity for additional hypotheses on the determinants of nonmetropolitan county growth that could inform future OLS (global) specifications. For example, in some regions, does the observed association between greater college attainment and the subsequent *ceteris paribus* decline in employment illustrate an interaction between low amenities and adverse demand shocks that expedite regional decline? Likewise, are there differences in out-migration responses of natives to immigration between the East and West? Or are natives moving out of the East for amenity reasons, vacating jobs and durable housing? These amenity effects could be examined for nonlinear and interactive effects in both GWR and OLS models in future research.

In choosing the preferred research methodology, researchers need to recognize the tradeoffs in using global approaches versus GWR. Global approaches are easier and there is much less output to interpret. Yet, even using GWR to inform the choice of more/better regional/spatial interactions, global approaches still require sufficient degrees of freedom. A further tradeoff is that unless the researcher uses an inordinate number of interaction terms, there still is spatial heterogeneity that is not being fully accounted for. For example, interacting (say) the college graduate share with a northeast dummy may not fully capture the heterogeneity of responses *within* the northeast.

In summary, the estimated heterogeneity in growth dynamics cautions against using only global regression approaches. Factors may be significant in opposite ways across regions, but average to zero across the entire spectrum. In addition, local economic development policymaking should be informed by knowledge of local socioeconomic processes, which calls for the use of statistical approaches capable of reflecting spatial heterogeneity in these processes. Estimated spatial heterogeneity also may generate new hypotheses to test and we have shown how global approaches can be augmented to reduce their specification biases by using GWR models as an exploratory tool. Finally, our finding that one size does *not* fit all suggests that regional models are sometimes simplistic in not recognizing the spatial heterogeneity in the underlying growth processes. More richness in our theoretical models appears to be needed to explain this diversity of regional results. We see geographically weighted regression as facilitating these research directions, providing a powerful tool to complement global regression analysis.

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Endnotes

[1] Kilkenny and Kraybill (2004) and Partridge and Rickman (2005) discuss circumstances where place-based policies can correct market failures and increase national efficiency.

[2]If panel data over time is available, then global approaches can use location-specific fixed effects to help account for spatial heterogeneity that is fixed over time (and not related to the other regression coefficients). However, this would not be possible with cross-section data, which is used in this paper.

[3]The 2003 definitions also allow us to use the newly defined micropolitan area category for some distance measures.

[4]This assumes that if (say) a nonmetro county borders counties in the New York City MA, its data generating process would likely have much more in common with other nonmetro counties even if those nonmetro counties are more distant than more proximate boroughs (counties) in the city (note, we control for cross-county spillovers).

[5]The weights in a bi-square decay function are specified as, $w_{ij} = [1-(d_{ij}/h_i)^2]^2$ when $d_{ij} \leq h_i$ and $w_{ij} = 0$ when $d_{ij} > h_i$, where d_{ij} is the distance between observations i and j and h_i is the bandwidth for observation i. Thus the regression weight quickly declines with distance from the geographic observation.

[6]Formally, as described above, county *i's* bandwidth is equal to n*, where n* is the 846 closest *rural* counties to *i* in the rural sample, while in the MA sample, n* is the nearest 893 MA counties.

[7]The 1990-2000 period, rather than 1990-2004 (corresponding with the dependent variable), is used in constructing the industry mix growth variable. This is due to the change from the SIC to the NAIC system. Thus, there could be some measurement error for not using the entire period which would bias the industry mix coefficient to zero. Yet,

the coefficient is very consequential, suggesting this is not a major concern.

[8]The BEA defines 179 regions that generally reflect functional economic areas centered on a larger urban center.

[9]Micropolitan areas and MAs are defined by the U.S. Census Bureau. Micropolitan areas are urban clusters (a ‘city’ or city plus immediately surrounding area) of 10,000-49,999 population plus counties with tight commuting linkages to this core. MAs are similarly defined, but the “city” must have at least 50,000 population.

[10]The significance of an individual county’s GWR coefficient is available from the authors upon request.

[11]The spatial error model followed specification, $\boldsymbol{y} = \boldsymbol{X\beta} + \boldsymbol{u}, \boldsymbol{u} = \lambda \boldsymbol{Wu} + \boldsymbol{\varepsilon}, \ \boldsymbol{\varepsilon} \sim N(0, \sigma^2 \boldsymbol{I})$, where λ is the spatial autocorrelation parameter, and $\boldsymbol{W}$ is the spatial-weight matrix that uses a row-standardized distance-based weights created using the inverse of squared distances—i.e., spillovers from more distant counties receive less weight. A bandwidth of 880 kilometer is chosen as a cut-off. Counties within this bandwidth retained the weight equal to the value of the inverse squared distance and counties outside this bandwidth received a weight of zero.

[12]Counties were classified as recreation counties based on factors such as their share of employment or share of earnings in recreation-related industries in 1999, share of seasonal or occasional use housing units in 2000, and per capita receipts from motels and hotels in 1997 (http://www.ers.usda.gov/Briefing/Rurality/Typology/).

[13]This education-amenity index interaction helps illustrate how GWR can inform subsequent analysis in standard approaches. Note that redefining the education variables as shares of the working age population (25-54 years) does not qualitatively change the results, in which the quantitative changes are insubstantial.

[14]The results of this analysis are not reported but available from the authors upon request.

[15]The results of this analysis are not reported but available from the authors upon request.

Table 1: Parameter Summary of Nonmetropolitan Area Employment Growth 1990-2004

Variables	Min	Lower quartile	Median	Global (OLS)	SEM (ML)	Upper quartile	Max
Explanatory variables:							
Average January temp***	-0.915	-0.141	0.161	0.125†	0.241††	0.567	0.976
Average January sun hours***	-0.231	-0.002	0.050	0.008	-0.023	0.081	0.230
Average July humidity***	-0.733	-0.133	0.088	-0.073	-0.034	0.220	0.567
Typography**	-0.159	0.069	0.394	0.152†	0.241††	0.531	0.707
% water area***	-0.235	0.055	0.205	0.161†††	0.101†	0.415	2.507
Agriculture share	-0.427	-0.102	0.036	-0.040	0.025	0.163	0.415
Goods share*	-0.422	-0.092	0.077	0.168†	0.044	0.223	0.501
% immigrated over 1985-90***	-5.767	1.558	3.209	1.923††	1.868††	6.759	15.233
% high school graduate**	-1.007	-0.462	-0.283	-0.236††	-0.098	-0.043	0.865
% some college**	-0.676	-0.133	0.216	0.518†††	0.543†††	0.868	1.209
% associate degree**	-2.607	-1.260	-0.453	-0.333	-0.073	0.161	1.022
% college graduate***	-0.517	-0.039	0.311	0.683†††	0.503†††	0.626	2.076
% African American**	-2.214	-0.891	-0.497	-0.289†††	-0.406†††	-0.429	-0.033
% Native American	-0.247	-0.029	0.075	0.122	0.117	0.171	1.220
% Asian-Pacific	-13.357	-7.229	-5.210	-5.981†††	-5.006†††	-2.058	2.050
% Hispanic***	-6.424	-2.972	-0.128	-0.044	-0.136	0.230	4.532
% other ethnicity***	-9.787	-1.232	-0.180	-0.491†††	-0.205	1.485	7.432
% under 6 years***	-1.992	-0.553	0.758	0.949†	1.070††	1.979	3.775
% 7-17 years	-3.140	-0.727	-0.329	0.145	-0.475	-0.142	0.607
% 18-24 years	-1.222	-0.589	-0.138	0.003	2.0E-04	0.473	0.949
% 55-59 years	-4.487	-0.282	0.580	1.007	0.685	1.634	2.881
% 60-64 years	-0.684	1.673	3.043	4.110†††	3.061†††	3.993	8.337
% over 65 years	-2.992	-2.007	-1.513	-1.732†††	-1.303†††	-1.179	-0.202
% unemployment**	-1.201	-0.494	-0.073	-0.507††	-0.007	0.628	1.617
Median HH income***	-0.003	-0.001	0.000	-0.001†††	-0.001†††	0.000	0.002
Population density 1990***	-0.210	-0.143	-0.110	-0.091†††	-0.101†††	-0.076	0.044
Industry mix emp growth*	85.308	138.455	194.006	204.22†††	179.74†††	226.237	269.608
1990 pop in surr counties***	-3.0E-06	-1.0E-06	0.000	-5.6E-07	-5.6E-07	2.0E-06	5.0E-06
% unemp in surr counties***	-2.685	-0.587	1.251	0.238	0.398	2.161	3.683
Median hh inc in surr counties*	-0.001	-3.2E-04	1.3E-04	3.0E-04	3.9E-04	0.001	0.002
Ind mix emp gr in surr counties	-171.21	-49.382	25.146	99.772	43.845	78.543	182.152
Pop of the nearest UC 1990*	-1.1E-05	-5.0E-06	4.0E-06	5.3E-6†††	9.0E-6††	1.5E-05	4.6E-05
Dist to nearest urban center*	-0.217	-0.142	-0.097	-0.103†††	-0.114†††	-0.072	-0.025
Inc dist to a metro***	-0.132	-0.082	-0.051	-0.055†††	-0.053†††	-0.031	0.021
Inc dist to metro>250,000 pop***	-0.107	-0.067	-0.041	-0.018†††	-0.023†††	-0.016	0.002
Inc dist to metro>500,000***	-0.153	-0.066	-0.040	-0.012†	-0.021†	-0.018	0.011
Inc dist to metro>1,500,000	-0.027	-0.013	-0.007	-0.009†	-0.005	-0.002	0.017
Intercept***	-121.29	-64.133	-15.687	-20.046	-14.261	26.871	185.065
No. of observations			1,972	1,972	1,972		
No. of nearest neighbors			846	n.a.	n.a.		
Adjusted R^2			0.45	0.30	0.28		
Akaike Information Criterion (AIC)			16,880.0	17,177.3	17,013.8		
F-stat of GWR improvement over OLS			4.38†††	n.a.	n.a.		
Spatial autocorrelation			n.a.	n.a.	0.72†††		

Notes: Nonmetro – Metro divisions are based on 2003 boundary definitions. See Appendix Table 1 for variable definitions. Unless otherwise indicated, all variables are measured in the initial period 1990. A ***, **, or * on variables indicate significant spatial variations in GWR coefficients of these variables at 1%, 5%, or 10% levels respectively, as determined by the Monte Carlo test described in Fotheringham et al. (2002) and Charlton et al. (2003). A †††, ††, or † indicate that the parameter is significantly different from zero at 1%, 5%, or 10% levels respectively.

Table 2: Parameter Summary of Metropolitan Area Employment Growth 1990-2004

Variables	Min	Lower quartile	Median	Global (OLS)	SEM (ML)	Upper quartile	Max
Explanatory variables:							
Average January temp**	0.386	0.816	0.985	0.657†††	0.654†††	1.096	1.221
Average January sun hours**	-0.098	-0.030	-0.016	0.213†††	0.212†††	0.115	0.306
Average July humidity***	-0.820	-0.348	-0.165	-0.356†††	-0.351†††	0.105	0.185
Typography**	-0.144	0.047	0.297	0.247	0.247	0.483	0.858
% water area	-0.224	-0.092	-0.072	-0.063	-0.065	-0.037	0.079
Agriculture share	1.838	2.593	2.949	2.453†††	2.452†††	3.441	4.025
Goods share**	-0.312	-0.119	-0.025	0.777†††	0.776†††	0.640	1.735
% immigrated over 1985-90***	-5.986	-2.168	1.720	-2.894	-2.859	5.080	6.397
% high school graduate	-1.687	-1.287	-1.019	-0.670†	-0.670†	-0.833	-0.244
% some college	-1.864	-0.993	-0.452	0.204	0.214	0.113	0.252
% associate degree	-2.111	-1.435	-0.741	-0.962	-1.007	-0.313	0.376
% college graduate***	-0.953	-0.806	-0.635	0.419	0.409	1.124	2.111
% African American	-0.691	-0.642	-0.569	-0.516†††	-0.517†††	-0.489	-0.139
% Native American***	-1.380	-0.245	0.850	-0.517	-0.511	1.783	2.780
% Asian-Pacific***	-9.393	-7.179	-6.099	-2.919†††	-2.896†††	-5.217	-1.964
% Hispanic***	-3.069	-2.258	-1.756	0.064	0.057	-0.161	0.709
% other ethnicity***	-4.190	-1.939	1.459	-2.272†††	-2.261†††	2.207	2.840
% under 6 years	-5.891	0.533	3.628	-1.872	-1.814	4.729	6.091
% 7-17 years	-2.659	0.010	0.515	-0.438	-0.404	1.549	2.663
% 18-24 years***	-6.465	-2.561	-0.183	-2.963†††	-2.926†††	0.826	1.955
% 55-59 years***	-27.733	-15.380	-2.204	-14.69†††	-14.55†††	-1.139	-0.083
% 60-64 years	-5.876	-1.451	0.202	-0.289	-0.323	1.010	1.803
% over 65 years	-6.323	-3.665	-3.359	-4.886†††	-4.836†††	-2.527	-0.686
% unemployment	-0.931	-0.163	1.293	1.282	1.299	3.612	5.699
Median HH income***	-0.001	0.001	0.001	0.000	-9.2E-05	0.002	0.004
Population density 1990***	-0.014	-0.005	0.000	0.001	0.001	0.001	0.001
Industry mix emp growth	268.812	306.673	313.346	377.07†††	378.68†††	342.580	451.429
1990 pop in surr counties***	0	0	1.0E-06	1.3E-07	1.2E-07	2.0E-06	3.0E-06
% unemp in surr counties	-5.813	-4.782	-3.854	-2.796††	-2.797††	-2.798	-1.890
Median hh inc in surr counties	-0.003	-0.002	-0.002	-0.002†††	-0.002†††	-0.002	-0.002
Ind mix emp gr in surr counties*	168.063	221.908	287.443	366.72†††	367.89†††	322.421	504.835
Pop of the nearest metro 1990***	-4.0E-06	-1.0E-06	-1.0E-06	5.6E-09	-6.4E-09	0	0
Dist to nearest urban center**	0.024	0.125	0.164	0.205†††	0.205†††	0.186	0.389
Inc dist to metro>250,000 pop	-0.084	-0.050	-0.039	-0.043††	-0.043††	-0.021	-0.009
Inc dist to metro>500,000	-0.044	-0.035	-0.028	-0.023	-0.023	-0.020	-0.001
Inc dist to metro>1,500,000*	-0.041	-0.018	-0.011	-0.022††	-0.022††	-0.003	0.009
Intercept	-110.343	-45.065	-0.584	112.62††	108.95††	75.015	244.606
No. of observations			1,057	1,057	1,057		
No. of nearest neighbors			893	n.a.	n.a.		
Adjusted R^2			0.42	0.33	0.35		
Akaike Information Criterion (AIC)			10,490.2	10,593.4	10,588.2		
F-stat of GWR improvement over OLS			4.54††	n.a.	n.a.		
Spatial autocorrelation			n.a.	n.a.	0.02		

Notes: Nonmetro – Metro divisions are based on 2003 boundary definitions. See Appendix Table 1 for variable definitions. Unless otherwise indicated, all variables are measured in the initial period 1990. A ***, **, or * on variables indicate significant spatial variations in GWR coefficients of these variables at 1%, 5%, or 10% levels respectively, as determined by the Monte Carlo test described in Fotheringham et al. (2002) and Charlton et al. (2003). A †††, ††, or † indicate that the parameter is significantly different from zero at 1%, 5%, or 10% levels respectively.

Figure Titles

Fig.1

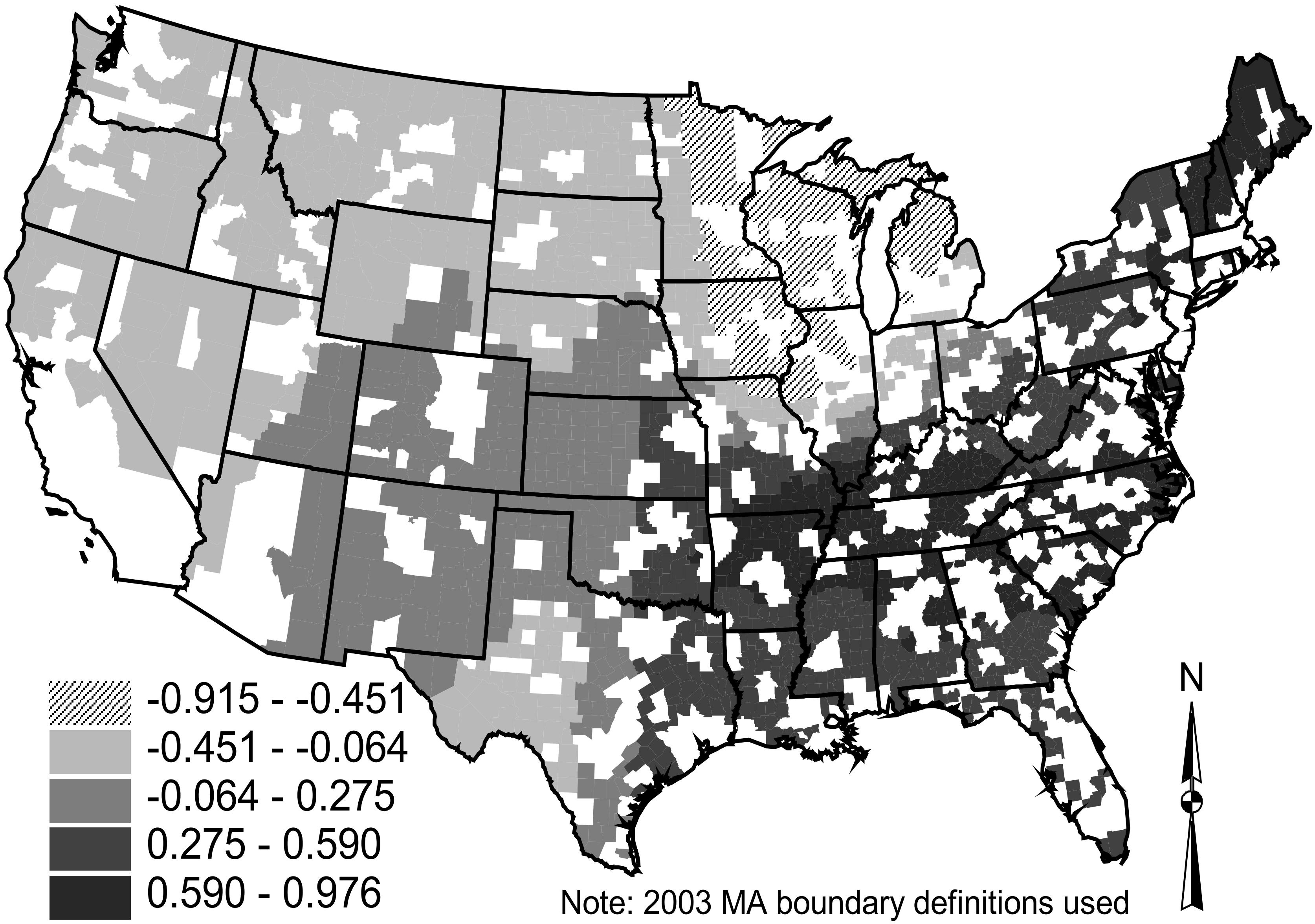
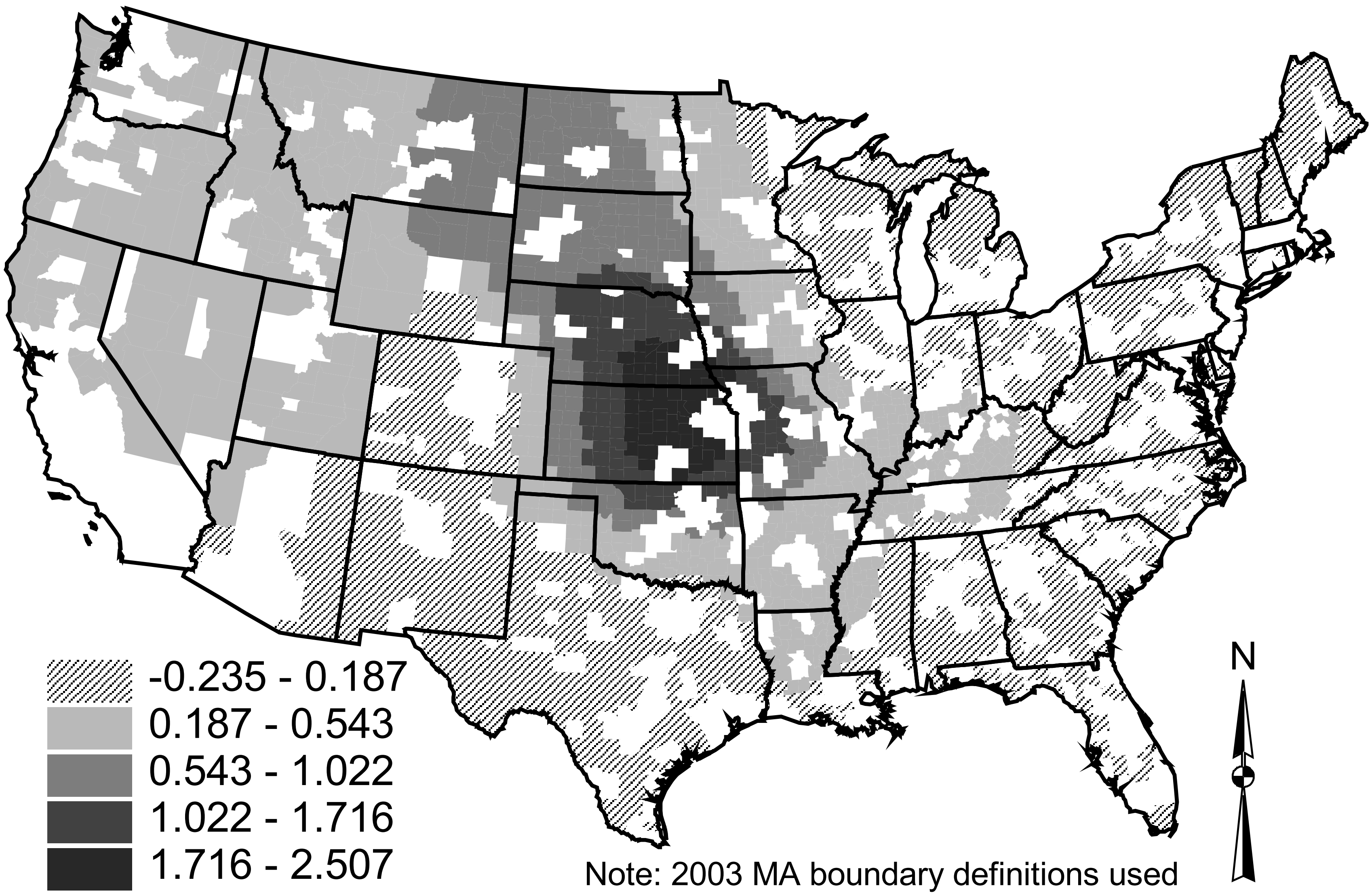

-0.915 - -0.451
-0.451 - -0.064
-0.064 - 0.275
0.275 - 0.590
0.590 - 0.976
Note: 2003 MA boundary definitions used
N

Fig. 2


-0.235 - 0.187
0.187 - 0.543
0.543 - 1.022
1.022 - 1.716
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Note: 2003 MA boundary definitions used
N

Fig. 3

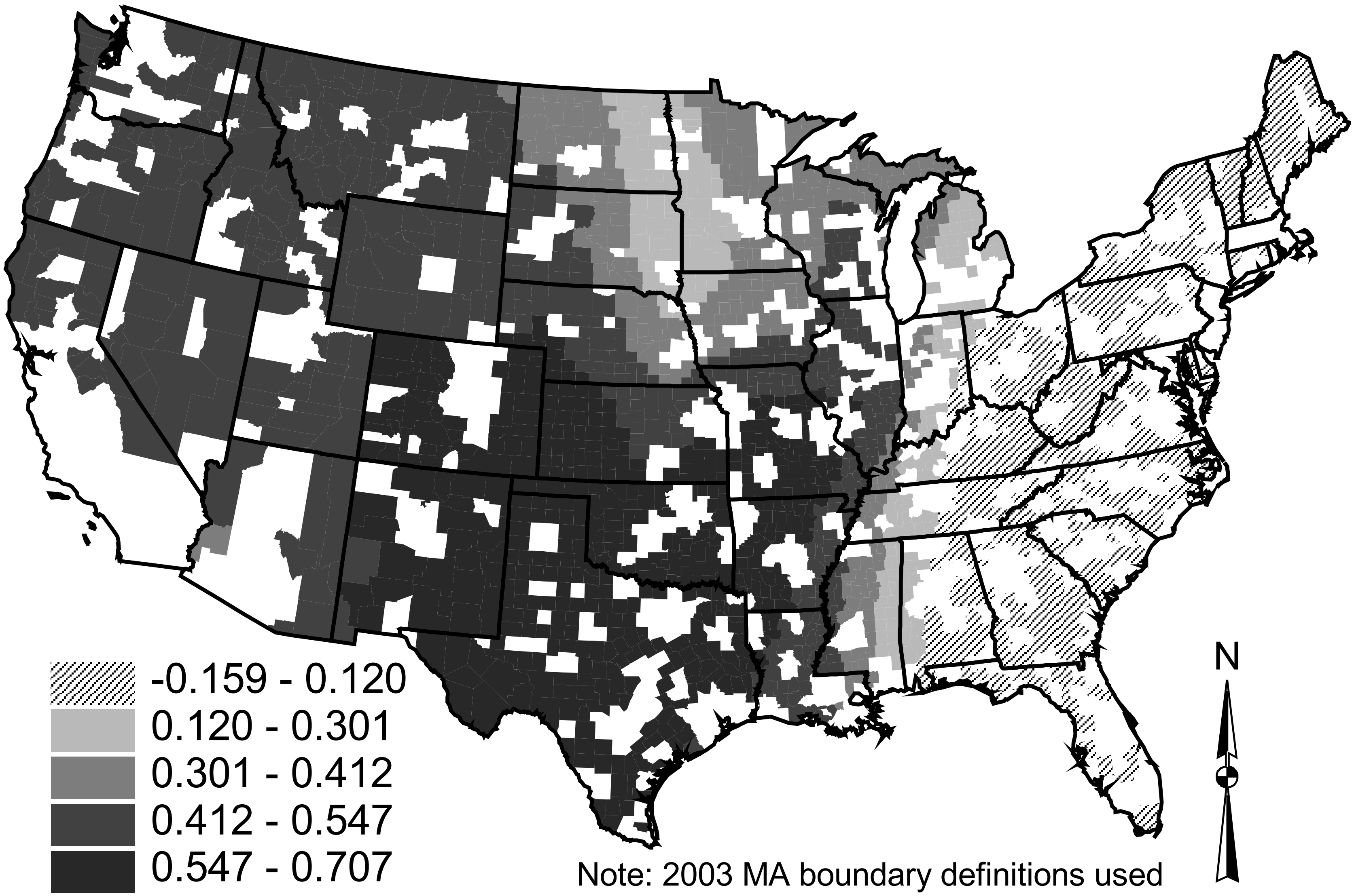

-0.159 - 0.120
0.120 - 0.301
0.301 - 0.412
0.412 - 0.547
0.547 - 0.707
Note: 2003 MA boundary definitions used
N

Fig. 4

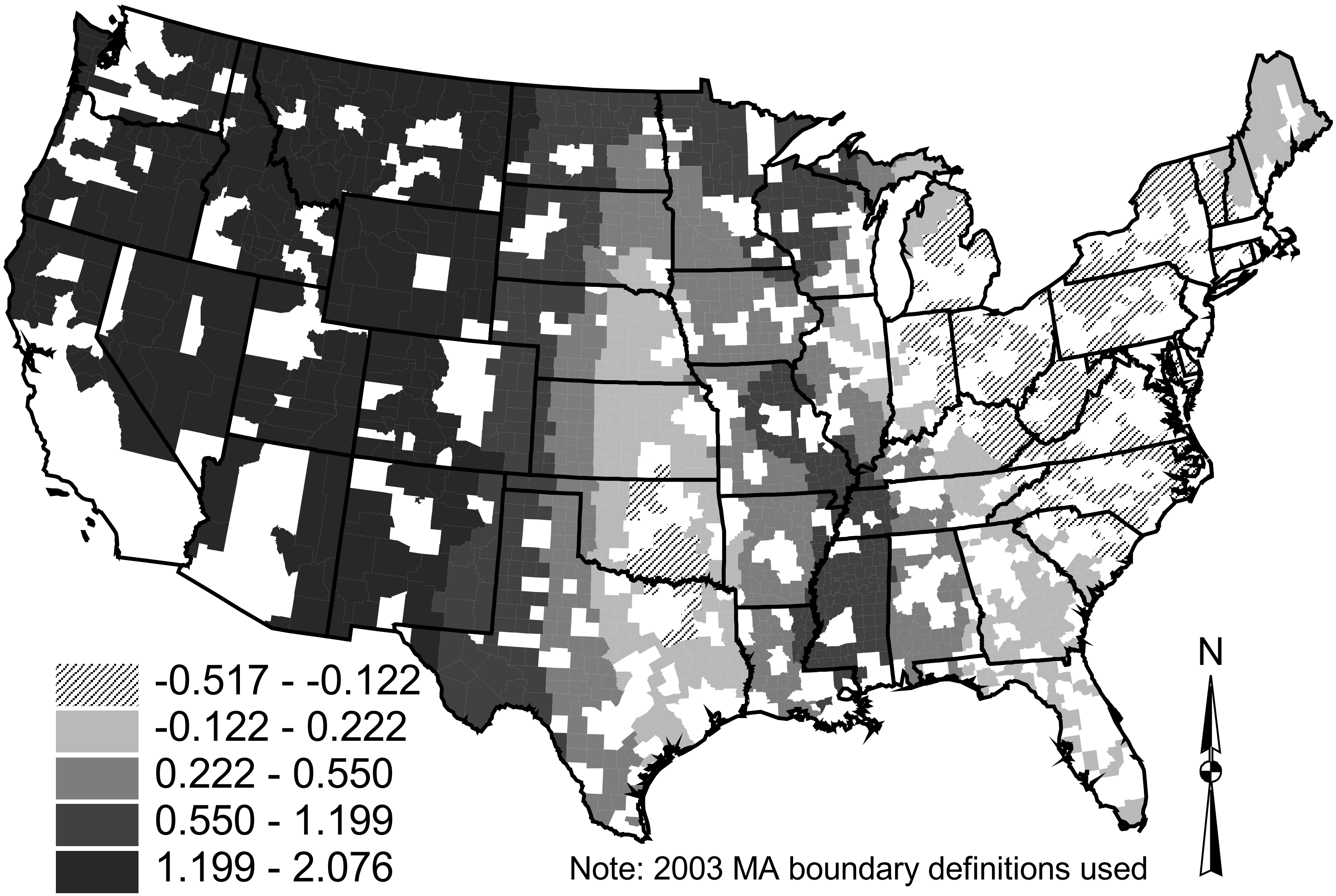

-0.517 - -0.122
-0.122 - 0.222
0.222 - 0.550
0.550 - 1.199
1.199 - 2.076
Note: 2003 MA boundary definitions used
N

Fig. 5

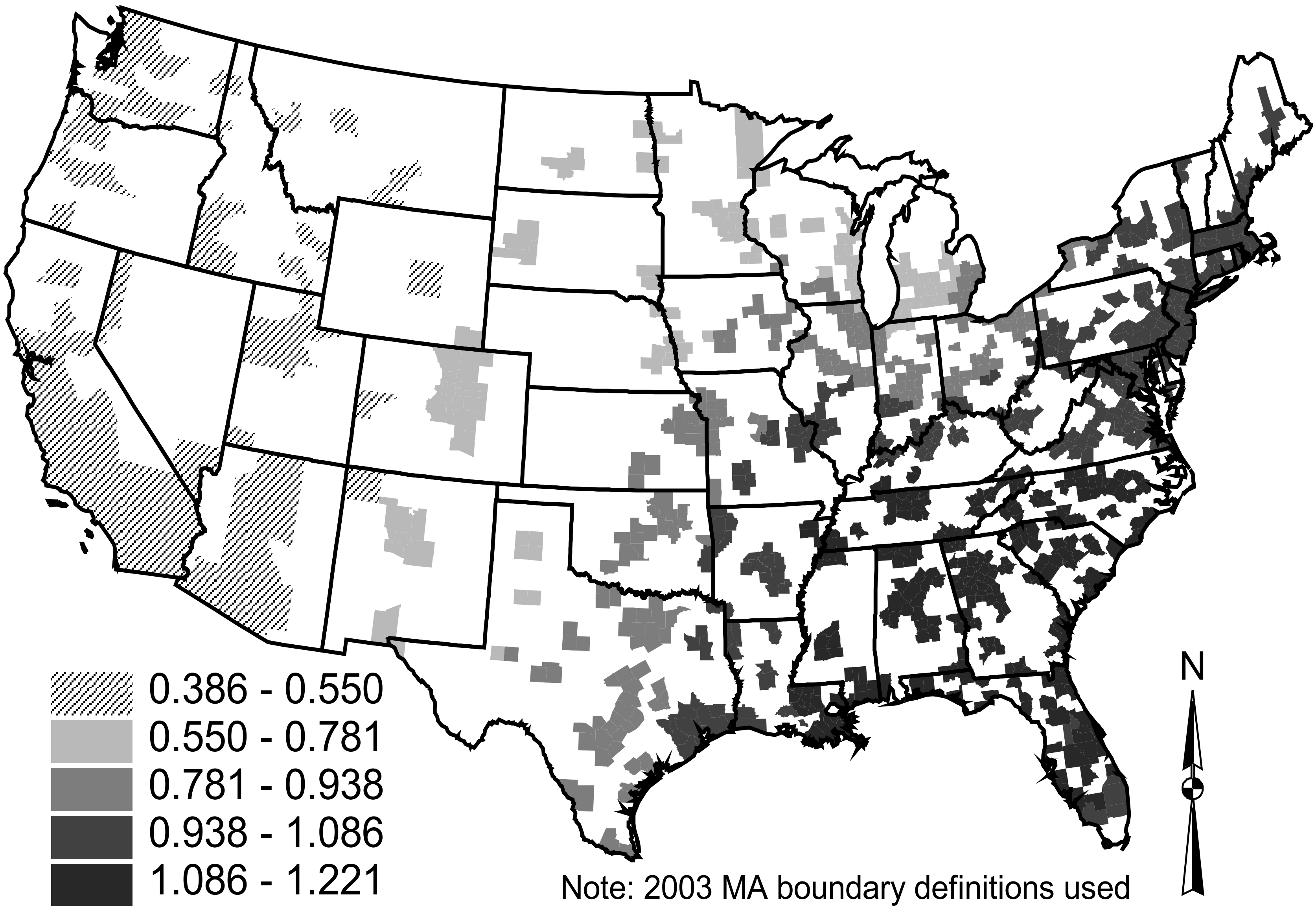
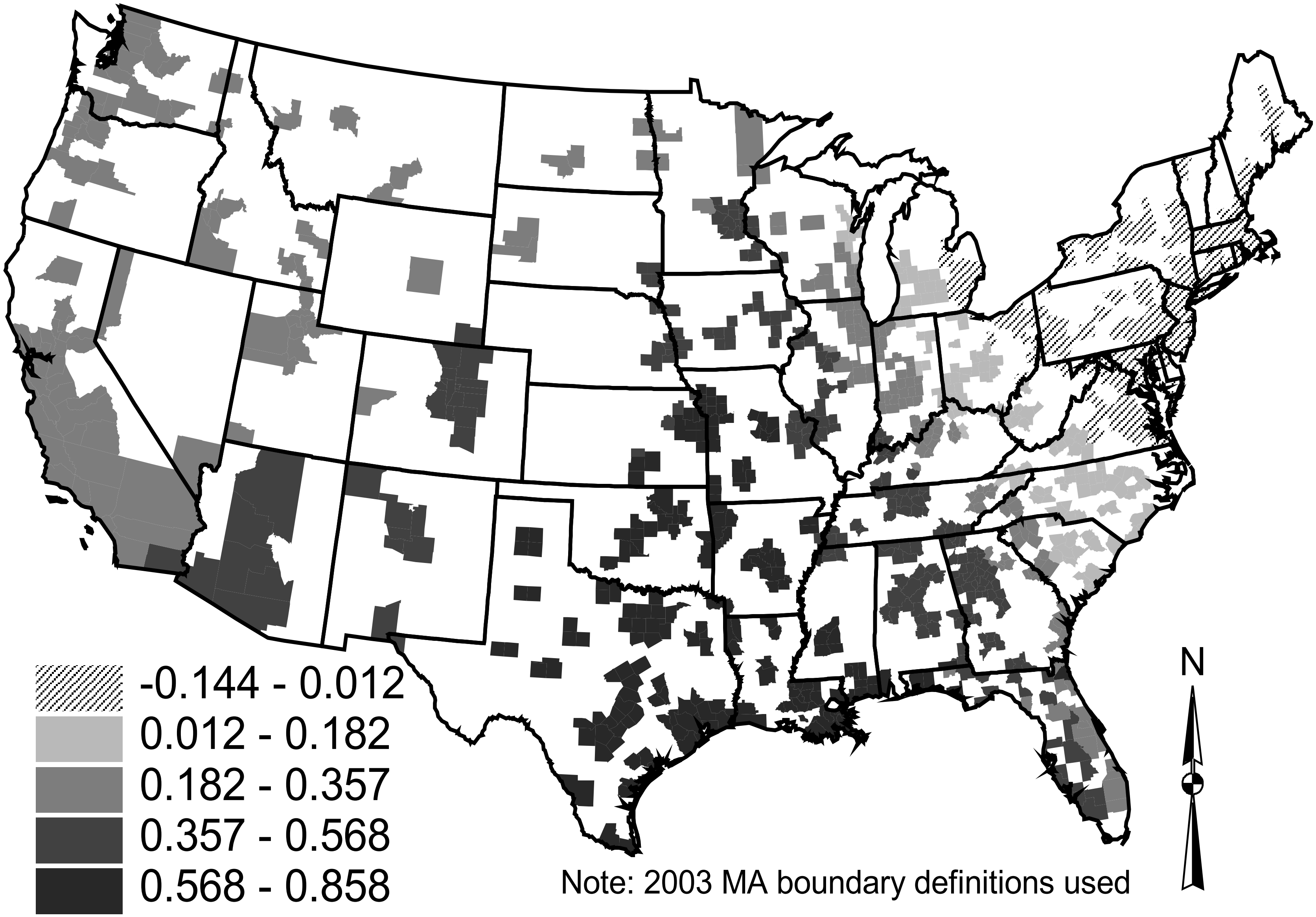

0.386 - 0.550
0.550 - 0.781
0.781 - 0.938
0.938 - 1.086
1.086 - 1.221
Note: 2003 MA boundary definitions used
N

Fig. 6


-0.144 - 0.012
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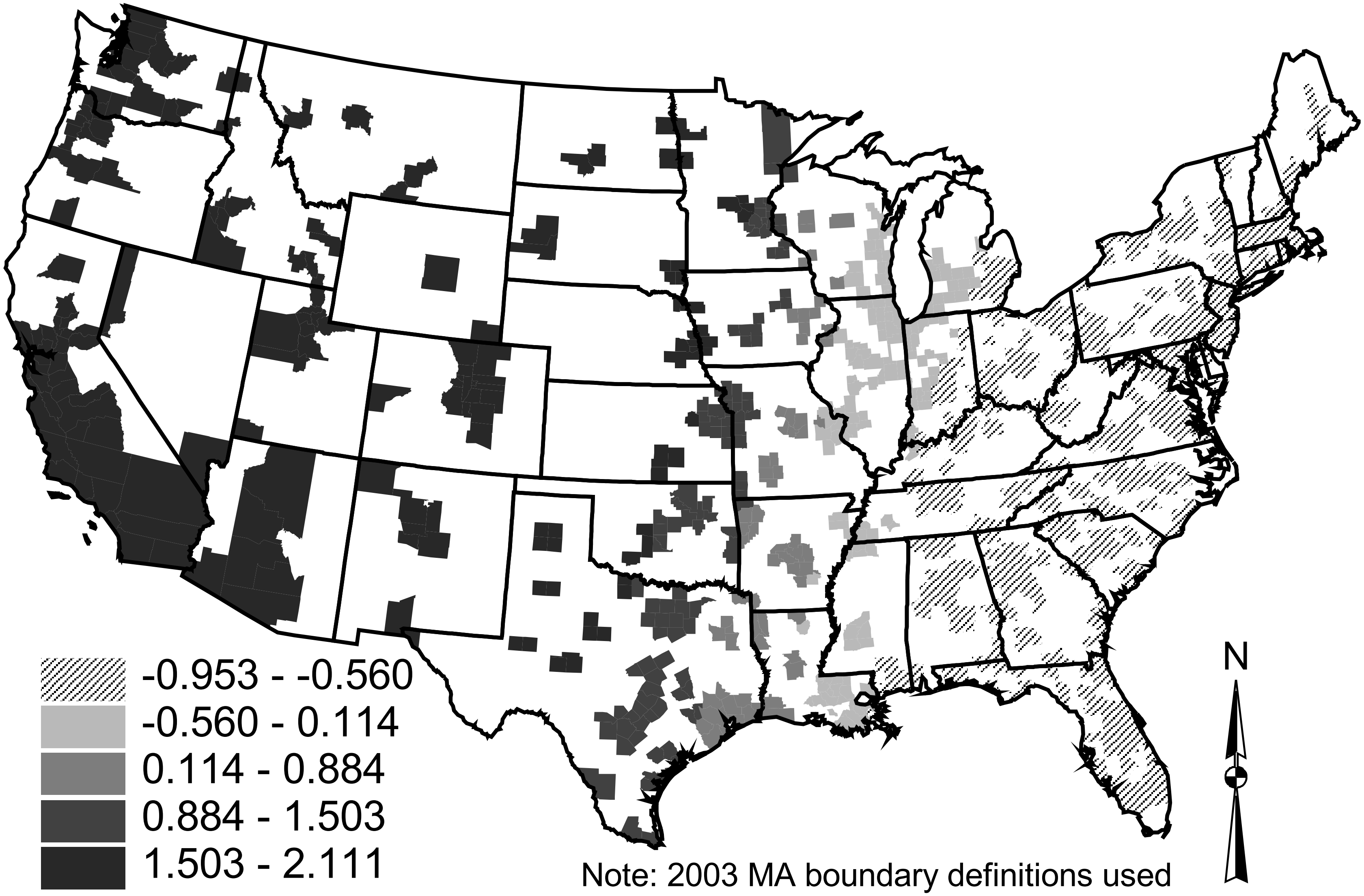
0.182 - 0.357
0.357 - 0.568
0.568 - 0.858
Note: 2003 MA boundary definitions used
N

Fig. 7


-0.953 - -0.560
-0.560 - 0.114
0.114 - 0.884
0.884 - 1.503
1.503 - 2.111
Note: 2003 MA boundary definitions used
N

Appendix Table 1: Variable Definitions and Descriptive Statistics

Variable	**Description**	**Source**	**Non-metro**		**Metro**	
			Mean	**St. dev**	**Mean**	**St. dev**
Dependent variable: % Employment change	Percentage change in total employment over 1990-2004	BEA, REIS	18.10	22.10	35.81	43.40
Dist to nearest/actual urban center (micropolitan or metropolitan area, CBSA)	Distance (in km) between centroid of a county and population weighted centroid of the nearest urban center, if the county is not in an urban center. It is the distance to the centroid of its own urban center if the county is a member of an urban center (in kms).	C-RERL	41.07	36.52	24.34	19.88
Inc dist to metro	Incremental distance to the nearest/actual metropolitan area in kms (see text for details)	Authors' est.	55.40	51.67	n.a.	n.a.
Inc dist to metro>250k	Incremental distance to the nearest/actual metropolitan area with at least 250,000 population in 1990 in kms (see text for details)	Authors' est.	66.80	106.20	36.69	74.12
Inc dist to metro>500k	Incremental distance to the nearest/actual metropolitan area with at least 500,000 population in 1990 in kms (see text for details)	Authors' est.	42.89	66.07	36.53	68.05
Inc dist to metro>1500k	Incremental distance to the nearest/actual metropolitan area with at least 1,500,000 population in 1990 in kms (see text for details)	Authors' est.	89.03	111.10	91.17	131.15
Population density	1990 county population per square mile	1990 Census	36.00	36.21	528.39	2668.28
Nearest/Actual Urban Center pop	1990 Population of the nearest/actual urban center measured as a micropolitan or metropolitan area (see text for details).	Authors' est.	65269.16	93265.43	1084595	2225581
Weather/Amenity						
Sun hours	Mean January sun hours	ERS, USDA	153.10	33.66	148.25	32.13
January temp	Mean January temperature (degree F)	ERS, USDA	31.61	12.26	35.45	11.28
July humidity	Mean July relative humidity (%)	ERS, USDA	54.42	14.75	59.37	13.41
Typography	Typography score 1 to 24, in which 24 represents the most mountainous terrain	ERS, USDA	9.02	6.63	8.46	6.50
Percent water	Percent of county area covered by water	ERS, USDA	3.52	9.83	6.65	13.37
Economic/Demographic						
Median HH inc	Median household income 1989	1990 Census	21356.07	4299.66	28481.88	7031.50
Industry mix growth	Industry mix employment growth, calculated by multiplying each industry's national employment growth (between 1990 and 2000) by the initial period (1990) industry employ. shares in each sector	1990, 2000 BEA, REIS Authors' est.	0.15	0.03	0.18	0.04
Unemployment rate	1990 Civilian unemployment rate (%)	1990 Census	6.97	3.35	6.10	2.18
Agriculture share	1990 Percent employed in agriculture sector	1990 Census	10.78	8.89	4.08	4.01
Goods share	1990 Percent empl. in (nonfarm) goods sector	1990 Census	27.26	11.05	27.32	8.37
Percent pop under 6 years	Percent of 1990 population under 6 years	1990 Census	9.99	1.51	10.25	1.32
Percent pop 7-17 years	Percent of 1990 population 7-17 years	1990 Census	17.08	2.32	16.21	2.27
Percent pop 18-24 years	Percent of 1990 population 18-24 years	1990 Census	8.59	3.32	10.28	3.36
Percent pop 55-59 years	Percent of 1990 population 55-59 years	1990 Census	4.70	0.74	4.30	0.63
Percent pop 60-64 years	Percent of 1990 population 60-64 years	1990 Census	4.93	0.97	4.28	0.86
Percent pop 65+ years	Percent of 1990 population over 65 years	1990 Census	16.27	4.11	12.53	3.63
Percent HS graduate	Percent of 1990 population 25 years and over that are high school graduates	1990 Census	35.00	5.96	33.17	6.23
Percent some college	Percent of 1990 population 25 years and over that have some college education	1990 Census	15.65	4.38	17.76	4.40
Percent associate degree	Percent of 1990 population 25 years and over that have an associate degree	1990 Census	5.15	2.20	5.70	1.85
Percent college graduate	Percent of 1990 population 25 years and over that are 4-year college graduates	1990 Census	11.75	4.73	16.56	7.91
Percent Hispanic	Percent of 1990 population Hispanic	1990 Census	4.34	11.65	4.43	9.58
Percent African American	Percent of 1990 population African-American	1990 Census	7.76	14.74	10.18	13.36
Percent Asian-Pacific	Percent of 1990 population Asian and Pacific islands origin	1990 Census	0.32	0.43	1.12	1.95

Percent Native American	Percent of 1990 population that are Native American	1990 Census	1.82	6.72	0.74	2.11
Percent other race	Percent of 1990 pop. with other race background	1990 Census	1.78	4.84	1.85	4.02
Percent immig 1985-90	Percent of 1990 pop. immigrated over 1985-90	1990 Census	0.33	0.69	0.75	1.28
Surrounding Variables						
Population_surr	Weighted average 1990 population in surrounding counties within a BEA region[a]	1990 Census, Authors' est.	1534795	1929331	2873835	3913925
Median HH inc_surr	Weighted average median household income in surrounding counties within a BEA region[a]	1990 Census, Authors' est.	25899.55	4266.32	28347.19	5298.06
Industry mix growth_surr	Weighted average industry mix employment growth in surrounding counties within a BEA region[a]	BEA, REIS Authors' est.	0.19	0.02	0.19	0.02
Unemployment rate_surr	Weighted average total civilian unemployment rate in surrounding counties within a BEA region[a]	1990 Census, Authors' est.	6.23	1.60	6.30	1.47
No. of counties			1,972		1,057	

Notes: Centroids are population weighted. The metropolitan/micropolitan definitions follow from the 2003 definitions. BEA = Bureau of Economic Analysis; REIS = Regional Economic Information System; ERS, USDA = Economic Research Services, U.S. Department of Agriculture; C-RERL = Canada Rural Economy Research Lab, University of Saskatchewan. See Partridge et al. (2006) for more details of the variable sources and sample selection.

[a]The surrounding BEA region variables are calculated as the average of the region net of the county in question. The BEA economic regions are the 179 functional economic areas in the contiguous U.S.