County Amenities and Net Migration

Anil Rupasingha and Stephan J. Goetz

U.S. county-level net migration data and a general spatial model are used to examine the effects of various amenities on migration decisions. Results suggest that higher county cancer risks and the presence of superfund sites in a county, or a higher ranking on the Environmental Protection Agency's hazard ranking system, reduce the relative attractiveness of a county to prospective migrants, while natural amenities on balance attract migrants, ceteris paribus. The results also reveal spatial dependence among contiguous counties in terms of net migration behavior.

Key Words: amenities, migration, spatial econometrics

Natural amenities such as open spaces, scenic lakes, rivers, beaches, mountain vistas, and mild temperatures are widely believed to be important factors considered by migrants, as are the types of amenities that are provided only in larger cities—such as Broadway musicals and theatre productions. While previous studies have examined the effects of natural and related amenities on migration (e.g., Knapp and Graves, 1989; Mueser and Graves, 1995), or population change (Deller et al., 2001), the effects on migration decisions of adverse local environmental and health conditions have been largely ignored in the literature.[1] Using a laboratory experimental setting, Greenwood, McClelland, and Schulze (1997) found that the presence of a nuclear waste facility in Yucca Mountain in Nevada may affect employment-related migration decisions, for example. Our study expands upon this and other previous work on the determinants of (net) migration using U.S. county-level data by systematically including health and environmental risks in migration decisions. An important methodological improvement is the use of spatial econometrics.

More formally, we use a utility-maximizing framework which includes health status and environmental quality as arguments in migrants' utility functions. Aggregating from the individual household to the county as the representative (average) net migrant, it is hypothesized that net population in-migration into an area depends on amenities, health factors, and environmental conditions at the beginning of the period over which net migration is measured, in addition to the conventional push and pull factors used in previous migration studies. The county-level cancer risk rate (associated with hazardous air pollutants), presence of superfund sites in a county and their relative potential to pose a threat to human health or the environment, and McGranahan's (1999) amenity index are used to represent health and environmental risks, and natural amenities, respectively. We assume the cancer risk rate and superfund variables measure two separate health risks, although one of the potential risks posed by superfund sites is a higher cancer risk rate. While the cancer risk rate measures the risk of developing cancer due to lifetime exposure to outdoor hazardous air pollutants, the risks posed by most superfund sites are related to water quality.[2]

Anil Rupasingha is assistant professor of economics at the American University of Sharjah, United Arab Emirates. Stephan J. Goetz is professor of agricultural and regional economics at Penn State University, and director of the Northeast Regional Center for Rural Development. Earlier versions of the manuscript were presented at the annual meetings of the Western Regional Science Association and the Northeastern Agricultural and Resource Economics Association. The research was supported in part by USDA National Research Initiative Grant No. 00-35401-9320.

[1] A notable exception is an environmental Kuznets curve study by Gawande, Berrens, and Bohara (2001). They incorporate hazardous waste sites as a determinant of migration.

[2] We are grateful to an anonymous reviewer for pointing this out.

Despite the recognition of the significance of space in earlier migration studies, most migration studies have not considered spatial dependence bias in the econometric modeling. This is largely due to the fact that these studies focused on states, provinces, or major regions, in which less spatial autocorrelation would be expected. Furthermore, many of these investigations included fixed effects for their units of analysis, which can capture persistent spatial relationships.

In our case, spatial dependence can arise for two major reasons. First, counties or units of government, as standard planning jurisdictions, often do not correspond to the identifiable geography of markets (such as a labor market). In particular, economic data do not always match the spatial scale of the phenomenon under study, such as the geographic extent of a "market" (Anselin, 2001), and the data may therefore contain a measurement error (LeSage, 1999). Second, spatial dependence may arise because of "the existence of a functional relationship between what happens at one point in space and what happens elsewhere" (Anselin, 1988, p. 11). For example, migration changes in one locality are likely to be affected by changes in characteristics of other localities, particularly those that are contiguous (Cushing and Poot, 2004). It is possible one locality is attracting migrants for the simple reason that its neighboring localities are attracting migrants. In contrast, shocks in the factors affecting migration decisions, such as unemployment, may be transmitted across county borders, thereby causing spatial dependence which in turn leads to model misspecification (Anselin, 1988) and biased and inconsistent OLS estimates (LeSage, 1999). Recently developed methods of spatial data analysis are used here to evaluate empirically the spatial effects that may arise in population movement across U.S. counties.

Previous Literature

Migration and health are related in a number of ways, yet only a few studies in the economics literature focus on both of these variables (Graves and Knapp, 1988; Conway and Houtenville, 1998; Gale and Heath, 2000). These studies are concerned primarily with the relationship between health care services or expenditures and retirement migration. Sociologists have investigated the effects of health and health care services on elderly migration, but have not considered other migration determinants (Cowper and Longino, 1992; Glasgow, 1995). In their laboratory (experimental) study, Greenwood, McClelland, and Schulze (1997) analyze the importance of "natural and man-made hazards" in migration decision making. Other migration studies incorporating environmental pull factors focus only on natural amenities (Knapp and Graves, 1989; Mueser and Graves, 1995).

While a few migration studies explicitly address spatial interaction, none use a spatial weights matrix to correct for spatial dependence bias in the econometric analysis. For example, Molho (1984) uses the length of county borders to control for contiguity effects. Boots and Kanaroglou (1988) incorporate a spatial structure into a nested logit model of migration within metropolitan Toronto. They create a spatial contiguity matrix by partitioning the study area into zones and test for spatial effects with a variable measuring distance between two zones. Jackman and Savouri (1996) investigate the effects of distance and contiguity on migration in the UK, measuring the distance between two regions as the number of highway miles between the largest towns of the regions. In another UK migration study, Wall (2001) uses the number of residents living in the region bordering adjacent regions to control for contiguity effects.

The Empirical Model

For the empirical implementation, we develop a reduced-form expression for aggregate net migration (M_i) as a function of amenities, disamenities, and other migration pull and push factors that have been used in the literature. In particular, we postulate for each county, *i*:

$$(1) \quad M_i = f(A_i, P_i),$$

where A_i denotes (dis-)amenities, and P_i is other migration determinants (controls). With the number of households in each county normalized at 1, it is hypothesized that net migration is a function of the cancer risk rate, whether or not the location has a superfund site, natural and other amenities (including the incidence of serious crime), population density, whether the county is urban or rural, as well as the traditional determinants of migration including expected income, age, local taxes and expenditures, and industrial structure. The latter is the proportion employed in agriculture and extractive industries, construction, manufacturing, transportation, retail and wholesale trade, and finance, insurance, and real estate. Potential endogeneity problems are addressed by using beginning-of-period values for explanatory variables.

Data

This section describes the data sources for each variable. Definitions of variables and descriptive statistics are presented in table 1. The Environmental Defense (ED) organization ranks counties based on the cancer health risks associated with estimated exposure to 148 hazardous air pollutants.[3] The index refers to an "average individual's added cancer risk" (per 1,000,000), which is the individual's estimated additional risk of getting cancer due to lifetime exposure to outdoor hazardous air pollutants in a county. The goal of the Clean Air Act is to reduce lifetime cancer risks from hazardous air pollutants to one in one million, and ED expresses added cancer risk in these units. For example, an added risk of 100 per 1,000,000 is 100 times higher than the Clean Air Act's goal. These rankings are based on Environmental Protection Agency (EPA) exposure estimates derived from 1990 emissions data; they provide a perspective on the magnitude and sources of hazardous air pollution problems and are not definitive evaluations of health risk in a particular locale. ED cautions readers that these calculations are based on models and are not necessarily predictive of a given individual's actual risk of getting cancer.

The superfund data for 1990 were obtained from the Environmental Protection Agency's website and represent the total number of superfund sites in a county on the National Priority List (NPL) in 1990. In a second set of regressions, we use the EPA's Hazard Ranking System (HRS) as an alternative measure to estimate the impact of the relative potential of superfund sites to pose a threat to human health or the environment. The HRS assigns each site a score ranging from 0 to 100, and sites receiving HRS scores of 28.5 and above are eligible for inclusion on the NPL. The HRS assigns numerical values to factors that relate to risk based on conditions at the site. These factors are grouped into three categories: (*a*) the likelihood that a site has released or has the potential to release hazardous substances into the environment; (*b*) characteristics of the waste (e.g., toxicity and waste quantity); and (*c*) people or sensitive environments (targets) affected by the release.

Several other natural and non-natural amenity variables are also included in the regression. The serious crime per capita variable from *USA Counties on CD* [U.S. Department of Commerce (USDC)/Bureau of the Census, 1998] is included for 1990. Per capita 1990 establishment counts of amusement and recreational facilities (SIC 7900) and museums, zoological and botanical gardens (SIC 8400) are extracted from the *County Business Patterns* CD (USDC/Bureau of the Census, 1990) and normalized by population [Deller et al. (2001) present an alternative set of amenity measures].

The county-level natural amenity variables are from McGranahan (1999) and are assumed to be invariant over time (see also Mueser and Graves, 1995). These variables include the average January temperature measured over the period 1941–1970, average days of sunshine in January (1941–70), mean temperature for July (1941–70), mean humidity levels in the summer (1941–70), the amount of water area as a percentage of total county area, and a topography scale compiled from the *National Atlas of the United States of America*. The latter variable is motivated by Power and Barrett (2001, p. 106), who also list "school quality, personal security, cultural and recreational opportunities, and the health of the natural and social environments" as features sought after by migrants.[4] In addition, we include population density in both linear and quadratic forms as a measure of quality of life. In particular, migrants are attracted either to the amenities only densely settled places can offer (Rappaport and Sachs, 2002), or to places with few people per square mile, ceteris paribus.

Based on the previous literature, the other explanatory variables are hypothesized to affect net migration rates as follows. Migrants are attracted to areas with higher expected real incomes. Todaro's (1969) formula is used to calculate this variable:

$$(2)\quad Y = \left([(1 - U) \times MHI]/COL\right) \times 100,$$

where U is the 1990 average unemployment rate and $(1 - U)$ represents the expected probability of employment (Saltz, 1998); *MHI* is median household income in 1989; and *COL* is the 1990 cost of living, expressed as an index (100 = average). Since reliable cost-of-living indices are not available at the county level, state-level cost of living data from McMahon (1991) are used to discount household

[3] Interested readers can refer to the Environmental Defense online ranking index at http://www.scorecard.org/ranking.

[4] Our attempts to include various measures of county-level school quality were not successful (we suspect because of endogeneity issues).

Table 1. Definitions of Variables and Descriptive Statistics

Variable	Definition	Mean	Standard Dev.	Min.	Max.
CANCER$RISK	Added cancer risk rate per million	112.50	74.28	0.00	950.00
SF$NPL	Superfund sites on National Priority List	0.39	1.28	0.00	23.00
HRS	Hazard Ranking System	8.36	17.55	0.00	90.33
CRMRTE90	Serious crimes known to police per 100,000 population, 1990	3,191.00	2,158.00	10.00	20,899.00
RECMBZ90	Amusement & recreational services and museums, botanical and zoological gardens per 10,000 people	3.17	3.16	0.00	53.76
JANTEM	Mean January temperature: 1947–70	32.90	12.01	1.10	66.80
JANSUN	Mean January hours of sun: 1947–70	151.50	33.05	48.00	266.00
TEMJULY	Mean July temperature: 1947–70	75.85	5.34	55.50	93.70
HUMDTY	Mean July relative humidity: 1947–70	56.15	14.59	14.00	80.00
WATAREA	Percent of water area	4.59	11.27	0.00	75.00
TOPOGRAP	Topography scale	8.89	6.60	1.00	21.00
POPDEN90	Population density, 1990	218.10	1,429.00	0.20	52,378.00
URBAN	Urban counties (metro counties) (0, 1)	0.27	0.44	0.00	1.00
RURAL	Rural counties (non-metro counties, not adjacent to metro) (0, 1)	0.41	0.49	0.00	1.00
RINC89	Expected real income, 1989 ($)	27,628.00	6,349.00	7,283.00	66,539.00
MEDAGE90	Median age, 1990	34.40	3.61	20.00	55.40
PCTAX87	Per capita local taxes, 1987 ($)	501.60	374.90	0.00	5,939.00
EXPTAX87	General expenditures/total taxes, 1987 (ratio)	3.45	1.90	0.66	36.31
AG90	Proportion employed in agriculture, forestry, fishing & mining	10.41	9.57	0.00	70.56
CONS90	Proportion employed in construction	6.86	2.28	0.00	21.57
MANU90	Proportion employed in manufacturing	18.58	10.56	0.00	53.67
TRANS90	Proportion employed in transportation	6.52	2.09	1.22	28.51
TRADE90	Proportion employed in trade	19.61	3.49	5.51	35.51
FIRE90	Proportion employed in finance, insurance & real estate	4.36	1.81	0.00	17.11
NENG	New England counties (0, 1)	0.02	0.15	0.00	1.00
MEST	Mideast counties (0, 1)	0.06	0.23	0.00	1.00
GLAK	Great Lakes counties (0, 1)	0.14	0.35	0.00	1.00
PLNS	Plains counties (0, 1)	0.20	0.40	0.00	1.00
SEST	Southeast counties (0, 1)	0.35	0.48	0.00	1.00
SWST	Southwest counties (0, 1)	0.10	0.30	0.00	1.00
RKMT	Rocky Mountain counties (0, 1)	0.07	0.25	0.00	1.00

incomes. Age is inversely associated with migration, because (retirement migration notwithstanding) the importance of locational and family ties increases with age (Ritsilä and Ovaskainen, 2001). Local taxes discourage in-migration (Saltz, 1998), holding constant local public expenditures per dollar of revenue. Agricultural communities and rural (nonmetropolitan nonadjacent) counties are expected to experience more net out-migration, as employment opportunities disappear over time, all else equal.

As in Meyer, Matthews, and Sommers (2001), a vector of seven indicator variables captures regional effects on migration. They correspond to the U.S. Bureau of Economic Analysis regions: New England, Mideast, Great Lakes, Plains, Southeast, Southwest, and Rocky Mountain, with Far West being the excluded category. In an alternative specification, this model is also estimated with state fixed effects. Income, unemployment, tax, industrial structure, and age data are from the U.S. Bureau of the Census and are, as indicated earlier, measured at the beginning of the period over which migration rates are calculated.

We use inter-county net migration rates for the period 1990–99, available from the Bureau of the Census, Population Division, which has compiled county population estimates and demographic components of population change as annual time series from July 1, 1990 to July 1, 1999. We are aware of the limitations of using net rather than gross (in and out) migration flows.[5] However, our focus here is the effect of a regressor on whether or not a county *on net* is losing or gaining population over time—in other words, are the forces at work in a county such that the county on balance loses or gains population through migration?

Methods

We start with the standard linear regression model, which assumes the variance of the disturbance term is constant:

$$(3)\quad \mathbf{M} = \mathbf{X}\boldsymbol{\beta} + \varepsilon,$$

where $\mathbf{M}$ is an $\{n \times 1\}$ vector of the net migration rate, and $\mathbf{X} = (\mathbf{A}, \mathbf{P})$ is an $\{n \times k\}$ matrix containing the determinants of migration. The vector $\boldsymbol{\beta}$ represents k parameters to be estimated for the explanatory variables, and ε is an i.i.d. vector of n residuals.

We consider three alternative specifications that allow for spatial dependence [see LeSage (1999) for further details]. One is the spatial autoregressive (SAR) model. This specification is relevant when the spatial dependence works through a spatial lag:

$$(4)\quad \mathbf{M} = \rho\mathbf{W}(\mathbf{M}) + \mathbf{X}\boldsymbol{\beta} + \varepsilon,$$
$$\varepsilon \sim N(0, \sigma^2 I_n),$$

where $\mathbf{M}$ denotes an $\{n \times 1\}$ vector of the migration (dependent) variable, $\mathbf{X}$ represents an $\{n \times k\}$ matrix containing the determinants of migration, and $\mathbf{W}$ is a spatial weights matrix. The scalar ρ is a spatial autoregressive parameter, and $\boldsymbol{\beta}$ denotes the k parameters to be estimated for the explanatory variables.

The second specification is the spatial error model (SEM). It is relevant when the spatial dependence works through the disturbance term:

$$(5)\quad \mathbf{M} = \mathbf{X}\boldsymbol{\beta} + u,$$
$$u = \lambda\mathbf{W}u + \varepsilon,$$
$$\varepsilon \sim N(0, \sigma^2 I_n),$$

where u is a disturbance term, and λ is a scalar spatial error coefficient.

If there is evidence that spatial dependence exists through both spatial lag and error terms, the general spatial model (SAC) is appropriate. LeSage (1999) suggests this model should be used if evidence exists of spatial dependence in the error structure from a SAR estimation. The SAC model includes both the spatial lagged term as well as a spatial error structure:

$$(6)\quad \mathbf{M} = \rho\mathbf{W}(\mathbf{M}) + \mathbf{X}\boldsymbol{\beta} + u,$$
$$u = \lambda\mathbf{W}u + \varepsilon,$$
$$\varepsilon \sim N(0, \sigma^2 I_n).$$

A spatial weights matrix represents the arrangements of counties relative to one another. It reflects the fact that spatial units which are near each other should exhibit a greater degree of spatial dependence than those more distant from each other (LeSage, 1999). We use triangles connecting the latitude-longitude coordinates in space to deduce contiguous entities (see LeSage, 1999).[6] The elements of spatial contiguity matrix $\mathbf{W}$ are:

$$(7)\quad W_{ij} = \frac{d_{ij}}{\sum_{j=1,\, i \neq j}^{n} d_{ij}},$$
$$\text{where } d_{ij} = \begin{cases} 1 & \text{if connected to } j, \\ 0 & \text{otherwise.} \end{cases}$$

Although most researchers accept the conceptual basis for incorporating spatial interaction into econometric models, empirical applications using large data sets have until recently been rare. Spatial data analysis requires the manipulation of $\{n \times n\}$ relations among n observations and uses operations such as determinants, eigenvalues, and inverses. Until recently it has not been possible to perform these operations on larger data sets such as those containing all U.S. counties. Recent developments offer promising procedures for incorporating spatial dependence in empirical models with larger data sets (Pace and Barry, 1997; LeSage, 1999). LeSage's Spatial Econometrics Toolbox for MATLAB[7] is in our experience the best software available to estimate spatial models with large data sets.

---

[5] Smith and Swanson (1998) make a case for using net migration data. Greenwood et al. (1991) discuss advantages and disadvantages of using gross versus net rates. Numerous recent studies have used net migration rates (e.g., Partridge and Rickman, 1999; Lewis, Hunt, and Plantinga, 2002; and Aronsson, Lundberg, and Wikström, 2001, among others).

[6] A nonzero entry in row i, column j in the contiguity matrix indicates counties i and j have borders that touch (or are "neighbors"); thus, these nonzero entries capture the contiguous relationship between adjacent counties. The first-order contiguity matrix is symmetric: if county i borders j, then j must also border i.

[7] This software is available online at http://www.spatial-econometrics.com.

Results

The first column pair of table 2 reports ordinary least squares (OLS) estimates with regional effects based on data from 3,104 U.S. counties, corrected for heteroskedasticity using the Breusch-Pagan adjustment. In the OLS model, most of the coefficient estimates are statistically significant at the 1% or 5% levels. All of the conventional variables (excluding regional variables) have the expected sign, except for age (*MEDAGE90*). Counties with higher expected real family incomes experienced greater rates of in-migration. Age has an unexpected positive sign, which contradicts previous findings that communities with proportionately more young residents attract in-migrants. Instead, these results imply counties with higher shares of young people lost more residents to out-migration than they gained due to in-migration, ceteris paribus. Conversely, counties with more elderly residents gained population due to net in-migration; this may reflect the increasing relative importance of retirement migration in the United States. Inclusion of a squared term for the age variable showed an inverse-U relationship (results are not reported here), which was not statistically significant.

Counties with higher local taxes experienced net out-migration of residents, confirming a Tiebout-type effect, while the expenditure/tax variable is not statistically significant. Counties with more workers in the agriculture, forestry, fishery, and mining sectors experienced more out-migration than in-migration. Counties with more construction, manufacturing, trade, and finance, insurance, and real estate activity attract migrants.

More importantly, coefficient estimates for both the cancer risk rate and superfund sites are statistically significant and negative (as expected). Thus, counties with higher cancer risk rates and hazardous waste sites are less attractive to migrants. The crime variable is highly significant and negative, indicating serious crime is a significant deterrent to migrants. Recreational and amusement services and museums, zoological and botanical gardens have no statistically significant effect on net county migration. Counties with moderate temperatures, lower humidity levels, and more interesting topography are attractive to migrants. It is notable that the coefficient for the Rocky Mountains census region is statistically different from zero even after we control for all of the other regressors shown, which supports the argument in Power and Barrett (2001). Population density has a U-shaped relationship with net migration, as expected. The results also show that rural areas lost more population to net out-migration (or attracted fewer in-migrants) than did their suburban counterparts over the period studied.

Column pair [2] of table 2 reports ordinary least squares (OLS) estimates with state effects. Basic results discussed above do not change except for four variables. They are transportation and trade sector employment, January sunshine, and urban variables. Trade sector employment is not statistically significant with state fixed effects, while the transportation sector employment, January sunshine, and urban variables become statistically significant with state fixed effects.

LeSage's (1999) Spatial Econometrics Toolbox for MATLAB is used to estimate the spatial models reported in the third (with regional effects) and fourth (with state effects) column pairs of table 2. We follow the criteria outlined by LeSage to select an appropriate spatial specification for our migration model. Since the general spatial model (SAC) nests both the SAR and the SEM, we first estimate the SAC model. The results of this estimation show that both the spatial autoregressive parameter (ρ) and the spatial error parameter (λ) are positive and highly significant, indicating the presence of both types of spatial effects. Therefore, the most suitable specification for our data is the SAC model. We also test the possibility that the disturbance structure involves higher-order spatial dependence. Over time, it is possible the initial spillover effects on neighbors work to influence more and more outlying entities (LeSage, 1999). Two specifications are tested, one with first-order and another with higher-order ($n = 2$) dependence. The specification with the first-order spatial weight matrix is found to better fit our data. The following inference is based on the general spatial model estimation.

Because the significant spatial parameter values indicate spatial dependence exists in our data, a model incorporating spatial effects is more appropriate for modeling U.S. county net migration. Although they are not directly comparable, the adjusted R^2 statistic increases from 0.43 (0.49 with state effects) in the OLS model to 0.50 (0.53 with state effects) in the SAC model (table 2). The trade sector variable that is statistically significant in the OLS model becomes insignificant in the spatial model. While all of the regional dummies are significant in the OLS model, the effects of the New England and Mideast regions are not significantly different from zero in the spatial model.

Table 2. Estimation Results with Superfund Sites (dependent variable = *Net Migration Rate*)

	[1] OLS Model (Regional Effects)		[2] OLS Model (State Effects)		[3] Spatial Model (Regional Effects)		[4] Spatial Model (State Effects)	
Variable	Coeff.	*t*-Ratio	Coeff.	*t*-Ratio	Coeff.	*t*-Ratio	Coeff.	*t*-Ratio
Constant	!23.641	3.60	!18.062	2.13	!22.449	4.15	!19.040	2.72
CANCER$RISK	!0.022	5.97	!0.023	6.67	!0.019	6.13	!0.022	6.78
SF$NPL	!0.714	5.58	!0.700	5.50	!0.661	4.57	!0.686	4.70
CRMRTE90	!4.8E-04	3.94	!0.001	4.70	!0.001	6.36	!0.001	6.83
RECMBZ90	!0.078	1.00	!0.088	1.22	!0.052	0.85	!0.067	1.11
JANTEM	0.250	6.90	0.296	5.28	0.198	5.68	0.285	5.14
JANSUN	!0.006	0.62	!0.050	3.64	!0.006	0.89	!0.034	3.01
TEMJULY	!0.342	4.16	!0.242	2.32	!0.266	4.16	!0.228	2.78
HUMDTY	!0.119	4.35	!0.141	4.13	!0.111	4.58	!0.128	3.91
WATAREA	0.021	1.20	!0.004	0.20	0.009	0.56	!0.009	0.55
TOPOGRAP	0.147	3.98	0.206	5.28	0.091	2.77	0.159	4.44
POPDEN90	!0.240	5.28	!0.206	4.74	!0.218	7.42	!0.193	6.46
POPDENSQ	0.001	4.50	4.7E-04	4.24	4.9E-04	7.17	4.4E-04	6.32
URBAN	0.593	0.99	1.029	1.76	0.768	1.49	1.083	2.13
RURAL	!1.722	4.18	!1.757	4.40	!1.427	3.42	!1.545	3.72
RINC89/100	0.046	7.69	0.042	6.54	0.040	10.45	0.040	9.39
MEDAGE90	0.654	9.78	0.616	9.32	0.590	11.32	0.589	11.00
PCTAX87	!0.003	2.40	!0.003	2.04	!0.003	4.21	!0.003	4.12
EXPTAX87	0.130	0.73	0.022	0.12	0.122	1.12	0.033	0.27
AG90	!0.201	4.36	!0.204	4.25	!0.157	4.35	!0.179	4.85
CONS90	1.767	13.48	1.717	13.58	1.542	17.24	1.573	17.55
MANU90	0.120	3.53	0.065	1.94	0.092	3.29	0.057	1.91
TRANS90	0.145	1.27	0.198	1.80	0.127	1.50	0.179	2.11
TRADE90	0.141	1.87	0.039	0.54	0.095	1.48	0.027	0.42
FIRE90	1.093	4.79	1.150	5.55	1.034	7.91	1.080	8.21
NENG	!3.715	2.84			!1.967	1.25		
MEST	!2.101	2.04			!0.741	0.62		
GLAK	3.375	3.57			3.011	2.93		
PLNS	3.689	3.83			3.290	3.17		
SEST	2.669	2.86			2.227	2.39		
SWST	2.443	2.31			1.932	2.18		
RKMT	8.876	6.26			6.776	6.63		
Rho (ρ)					0.330	13.02	0.244	6.80
Lambda (λ)					0.051	7.02	0.041	4.09
Adjusted R^2	0.430		0.490		0.500		0.530	
Log-Likelihood Statistic	!12,247		!12,247		!6,798		!6,683	

The significant spatial parameters have interesting implications. A significant spatial dependence in the dependent variable (net migration rate) indicates that the net migration in a particular county relates to net migration rates in its surrounding counties. Based on the value of the spatial autocorrelation coefficients (ρ = 0.33), a 10% increase in the net migration rate into a county results in a 3.3% increase in net migration in a neighboring county. This is strong evidence that spillover effects exist between counties with respect to migration. The highly significant spatial error coefficients in the SAC model (λ = 0.05) suggest that a random shock which affects migration in a particular county can

Table 3. Estimation Results with HRS Score (dependent variable = *Net Migration Rate*)

	[1] OLS Model (Regional Effects)		[2] OLS Model (State Effects)		[3] Spatial Model (Regional Effects)		[4] Spatial Model (State Effects)	
Variable	Coeff.	*t*-Ratio	Coeff.	*t*-Ratio	Coeff.	*t*-Ratio	Coeff.	*t*-Ratio
Constant	!22.210	3.41	!16.274	1.92	!21.167	3.94	!17.334	2.51
CANCER$RISK	!0.022	6.02	!0.023	6.64	!0.019	6.23	!0.022	6.81
HR	!0.062	5.59	!0.051	4.94	!0.057	5.46	!0.051	4.97
CRMRTE90	!4.5E-04	3.64	!0.001	4.47	!0.001	6.08	!0.001	6.60
RECMBZ90	!0.078	1.01	!0.086	1.21	!0.051	0.84	!0.065	1.07
JANTEM	0.249	6.90	0.294	5.24	0.196	5.67	0.283	5.10
JANSUN	!0.006	0.68	!0.051	3.73	!0.007	0.97	!0.035	3.10
TEMJULY	!0.346	4.24	!0.250	2.38	!0.268	4.22	!0.236	2.88
HUMDTY	!0.124	4.49	!0.149	4.37	!0.114	4.75	!0.136	4.16
WATAREA	0.024	1.40	!1.74E-04	0.01	0.013	0.76	!0.006	0.35
TOPOGRAP	0.153	4.13	0.211	5.39	0.096	2.92	0.162	4.60
POPDEN90	!0.249	5.30	!0.213	4.70	!0.226	7.71	!0.200	6.68
POPDENSQ	0.001	4.51	4.9E-04	4.21	0.001	7.48	4.6E-04	6.56
URBAN	0.695	1.15	1.090	1.85	0.862	1.67	1.151	2.27
RURAL	!1.785	4.34	!1.813	4.55	!1.479	3.56	!1.595	3.86
RINC89/100	0.045	7.66	0.042	6.48	0.039	10.26	0.039	9.23
MEDAGE90	0.649	9.73	0.612	9.27	0.584	11.26	0.584	10.94
PCTAX87	!0.003	2.41	!0.003	2.04	!0.003	4.29	!0.003	4.18
EXPTAX87	0.113	0.64	0.010	0.05	0.108	1.00	0.023	0.19
AG90	!0.216	4.68	!0.216	4.48	!0.169	4.70	!0.190	5.18
CONS90	1.764	13.51	1.718	13.60	1.534	17.31	1.570	17.81
MANU90	0.112	3.32	0.059	1.75	0.085	3.04	0.050	1.69
TRANS90	0.135	1.18	0.193	1.75	0.116	1.38	0.173	2.04
TRADE90	0.148	1.97	0.045	0.61	0.102	1.59	0.032	0.51
FIRE90	1.059	4.69	1.124	5.43	1.003	7.73	1.053	8.07
NENG	!3.427	2.64			!1.658	1.06		
MEST	!2.183	2.09			!0.808	0.69		
GLAK	3.524	3.71			3.141	3.07		
PLNS	3.798	3.93			3.390	3.28		
SEST	2.787	2.97			2.327	2.51		
SWST	2.429	2.30			1.914	2.17		
RKMT	9.014	6.36			6.882	6.79		
Rho (ρ)					0.336	16.88	0.249	11.17
Lambda (λ)					0.048	6.80	0.040	4.17
Adjusted R^2	0.430		0.490		0.500		0.520	
Log-Likelihood Statistic	!12,247		!12,247		!6,794		!6,682	

trigger a change in migration not only in that county but also in its neighboring counties.[8]

Results presented in table 3 address the issue of risk posed by the superfund sites. The Hazard Ranking System (HRS) developed by the EPA to assess the relative potential of superfund sites to

[8] As a check on the robustness of the results, a separate regression was run using 1990 to 1995 net migration rates, and the same independent variables and state fixed effects (results are not reported here, but are available from the authors upon request). All of the signs of the variables remained the same and significance levels of the variables remained largely unchanged, except that the shares of manufacturing and transportation employment were not significant in the new specification.

pose a threat to human health or the environment was incorporated into the model in place of the total number of superfund sites. Variable HRS, which is the average score for a county, was negative and highly significant statistically across various specifications such as OLS versus Spatial, and regional effects versus state effects. This result reveals that the information of potential risk posed by these superfund sites discourages in-migration. Effects of the other variables largely remained unchanged by the inclusion of HRS in the model.

Finally, according to the equations with state effects, the standardized beta coefficient for cancer risk (! 0.131) is in absolute terms larger than that for superfund sites (! 0.070) or—not surprisingly—the hazard rank system (! 0.072). Migrants thus react more strongly to a one-standard-deviation shock (signal change) in local cancer risk than a comparable shock to the superfund sites or the HRS. These standardized values are smaller than the value for the crime rate (0.173) but larger than the value for amusement and recreational services (0.017). On the other hand, the standardized effect of January temperature is larger (0.274) than that of any of these factors, including January sunshine (0.090), topography (0.084), or bodies of water (0.008).

Conclusion

This study provides new insights into the determinants of net migration among U.S. counties by introducing health and environmental risk factors as well as other natural and human-made amenity variables, along with spatial interaction effects, into the traditional model of migration. Results provide strong evidence that high health risks of a locality and the presence of hazardous waste sites discourage people from moving into an area. Conversely, migrants are attracted by the types of amenities featured in McGranahan's (1999) index, which include the variables emphasized by Power and Barrett (2001). Tests for spatial dependence bias revealed strong evidence of spatial spillover effects across county boundaries.

Although most natural amenities are readily observable (e.g., using weather maps on TV or land cover maps in public libraries), it has traditionally been more costly for individuals to discover potential health and environmental risks that exist in a county. Over time, the transactions costs involved in determining these risks are falling. For example, websites now make this kind of information readily available. One extension of this work in the future will be to determine whether the coefficient estimate on the health and environmental variable increases in size (in absolute value) over time, as it becomes less costly for individuals to identify these risks using the web.

References

Anselin, L. (1988). *Spatial Econometrics: Methods and Models.* Dordrecht: Kluwer Academic Publishers.

———. (2001). "Spatial Effects in Econometric Practice in Environmental and Resource Economics." *American Journal of Agricultural Economics* 83, 705–710.

Aronsson, T., J. Lundberg, and M. Wikström. (2001). "Regional Income Growth and Net Migration in Sweden, 1970–95." *Regional Studies* 35(9), 823–830.

Boots, B. N., and P. S. Kanaroglou. (1988). "Incorporating the Effects of Spatial Structure in Discrete Choice Models of Migration." *Journal of Regional Science* 28, 495–507.

Conway, K. S., and A. J. Houtenville. (1998). "Do the Elderly 'Vote with Their Feet?'" *Public Choice* 97, 663–685.

Cowper, D. C., and C. F. Longino, Jr. (1992). "Veteran Interstate Migration and VA Health Service Use." *Gerontologist* 32, 44–50.

Cushing, B., and J. Poot. (2004). "Crossing Boundaries and Borders: Regional Science Advances in Migration Modeling." *Papers in Regional Science* 83, 317–338.

Deller, S. C., T.-H. Tsai, D. W. Marcouiller, and D. B. K. English. (2001, May). "The Role of Amenities and Quality of Life in Rural Economic Growth." *American Journal of Agricultural Economics* 83(2), 352–365.

Gale, L. R., and W. C. Heath. (2000). "Elderly Internal Migration in the United States." *Public Finance Review* 28, 153–170.

Gawande, K., R. P. Berrens, and A. K. Bohara. (2001). "A Consumption-Based Theory of the Environmental Kuznets Curve." *Ecological Economics* 37, 101–112.

Glasgow, N. (1995). "Retirement Migration and the Use of Services in Nonmetropolitan Counties." *Rural Sociology* 60, 224–243.

Graves, P. E., and T. A. Knapp. (1988). "Mobility Behavior of the Elderly." *Journal of Urban Economics* 24, 1–8.

Greenwood, M. J., G. H. McClelland, and W. D. Schulze. (1997). "The Effects of Perceptions of Hazardous Waste on Migration: A Laboratory Experimental Approach." *Review of Regional Studies* 27, 143–161.

Greenwood, M. J., P. R. Mueser, D. A. Plane, and A. M. Schlottmann. (1991). "New Directions in Migration Research: Perspectives from Some North American Regional Science Disciplines." *Annals of Regional Science* 25(4), 237–270.

Jackman, R., and S. Savouri. (1996). "Regional Migration and the Hiring Function: An Examination of Distance and Contiguity Effects in Great Britain, 1975–92." In R. Schettkat (ed.), *The Flow Analysis of Labour Markets*. London: Routledge.

Knapp, T. A., and P. E. Graves. (1989). "On the Role of Amenities in Models of Migration and Regional Development." *Journal of Regional Science* 29, 71–87.

LeSage, J. P. (1999). *Spatial Econometrics.* Online. Available at http://www.rri.wvu.edu/WebBook/LeSage/spatial/spatial.html.

Lewis, D. J., G. L. Hunt, and A. J. Plantinga. (2002, May). "Public Conservation of Land and Employment Growth in the Northern Forest Region." *Land Economics* 78(2), 245–259.

McGranahan, D. A. (1999, September). "Natural Amenities Drive Rural Population Change." Ag Econ Report No. 781, USDA/Economic Research Service, Food and Rural Economics Division, Washington, DC.

McMahon, W. M. (1991). "Geographical Cost of Living Differences: An Update." *AREUEA Journal* 19, 426–450.

Meyer, D. A., P. H. Matthews, and P. M. Sommers. (2001). "Net Interstate Migration Revisited." *Applied Economics Letters* 8, 131–134.

Molho, I. (1984). "A Dynamic Model of Interregional Migration Flows in Great Britain." *Journal of Regional Science* 24, 317–337.

Mueser, P. R., and P. E. Graves. (1995). "Examining the Role of Economic Opportunity and Amenities in Explaining Population Redistribution." *Journal of Urban Economics* 37, 176–200.

Pace, R. K., and R. Barry. (1997). "Quick Computation of Spatial Autoregressive Estimators." *Geographical Analysis* 29, 232–247.

Partridge, M. D., and D. S. Rickman. (1999). "A Note on the Benefits to Current Residents of State Employment Growth: Is There an Industry Mix Effect on Migration?" *Journal of Regional Science* 39(1), 167–181.

Power, T. M., and R. N. Barrett. (2001). *Post-Cowboy Economics—Pay and Prosperity in the New American West.* Washington, DC: Island Press.

Rappaport, J., and J. D. Sachs. (2002, October). "The U.S. as a Coastal Nation." Publication No. RWP 01-11, Research Division, Federal Reserve Bank of Kansas City. [38+ pp.].

Ritsilä, J., and M. Ovaskainen. (2001). "Migration and Regional Centralization of Human Capital." *Applied Economics* 33, 317–325.

Roback, J. (1982). "Wages, Rents, and the Quality of Life." *Journal of Political Economy* 90, 1257–1278.

Saltz, I. S. (1998). "State Income Tax Policy and Geographic Labour Force Mobility in the United States." *Applied Economics Letters* 5, 599–601.

Smith, S. K., and D. A. Swanson. (1998). "In Defense of the Net Migrant." *Journal of Economic and Social Measurement* 24(3-4), 249–264.

Todaro, M. P. (1969). "A Model of Labor Migration and Urban Unemployment in Less Developed Countries." *American Economic Review* 59, 138–148.

U.S. Department of Commerce, Bureau of the Census. (1990). *County Business Patterns.* CD-ROM, Washington, DC.

———. (1998). *USA Counties on CD.* CD-ROM, Washington, DC.

Wall, H. J. (2001). "Voting with Your Feet in the United Kingdom: Using Cross-Migration Rates to Estimate Relative Living Standards." *Papers in Regional Science* 80, 1–23.