The Effect of U.S. School Quality on Migration: A Spatial Econometric Approach

Anita P. Yadavalli, Brigitte S. Waldorf, Raymond J.G.M. Florax
Department of Agricultural Economics, Purdue University

Abstract

Spatial dependence and spatial heterogeneity play a crucial role in determining the extent to which differences in school quality are a driver of migration processes. We examine the effect of primary and secondary educational expenditures on inmigration flows in the context of rurality. The analysis pertains to counties in the United States, during the period 2006 – 2010. We use several spatial econometric models and generally find school quality, as measured by per pupil expenditures, positively and significantly affects both urban and rural inmigration, but the magnitude of the effect on urban areas is larger.

Keywords: Migration, school quality, spatial econometric model
JEL codes: C21, H52, R23

1. Introduction

Individuals move in response to economic incentives and by comparison between the present value of the benefits and costs of moving (Bowles, 1970). The potential migrant is assumed to select the locality at which the real value of the expected net benefit that accrues to him from migration is the greatest, that is, at which he maximizes his utility. The framework most often associated with such behavior is the Tiebout (1956) model, which states that voters reveal their preferences for public goods by locating in jurisdictions that offer them an optimal mix of expenditures and taxes. Given that framework, it has proven valuable to examine whether school quality influences location choices (Pack, 1973; Liu, 1977; Cebula and Alexander, 2006; Cebula and Nair-Reichert, 2012).

In the context of Tiebout, educational expenditures should positively and significantly affect people's decisions to migrate. Concurrently, property taxes are expected to negatively influence people's decisions to move to another locality. Property value and migration models have been used to determine whether the Tiebout hypothesis of consumer location in accordance with preferences for local public goods and taxes is valid. Schools in the United States are funded largely by local property taxes, whereby a community may want to increase its property tax rate to expand its output of public services. Migrants are faced with the decision whether to migrate to a jurisdiction that offers them better school quality or lower property taxes.

In general, empirical migration literature that takes spatial sorting and spatial dependence, into account is sparse. As stated in Tobler's First Law of Geography (1979), "everything is related to everything else, but near things are more related than distant things." Distance has a strong negative effect on migration such that the farther the distance between two regions, the lower the flow of migrants between them (Schwartz, 1973). In this gravity-type modeling setup, it is thought that migration flows between a pair of regions are likely to be affected by changes in the characteristics of other regions, with more weight given to those nearby (Cushing and Poot, 2004). We contend that spatial dependence is prevalent among U.S. counties, as characteristics are transmitted across county borders and thus affect neighbor characteristics.

The purpose of this paper is to analyze the effect of school quality on in-migration flows and explicitly account for the spatial context. Spatial effects have been incorporated in the context of gravity models (LeSage and Pace, 2008; Fischer and Wang, 2011). In purely cross-sectional migration studies, however, the effect of socioeconomic characteristics of migrant i and labor market and geographic characteristics of area j are oftentimes simply regressed on migratory status (Folger and Nam, 1967; Somers and Suits, 1973; Schwartz, 1976; Navratil and Doyle, 1977; Saltz, 1998; Rayer and Brown, 2001; Cebula and Alexander, 2006).

The contributions of this work are twofold. First, we aim to understand whether school quality is indeed a determinant of migration. Though others have examined this relationship at the state level, we choose county data based on the assumption that more people move across counties for "better schools" than across states. Second, we introduce spatial effects to the traditional migration model to account for spatial dependence. We examine school quality in the context of urban/rural spatial regimes, which are very relevant given current depopulation trends in many rural areas of the United States and Europe.

We examine inmigration flows of U.S. couties during the period 2006-2010 and find that spatial heterogeneity and dependence among in-migration flows exists. We show that school quality, as measured by per pupil expenditures, positively and statistically significantly affects people's migration decisions for both the spatial Durbin and cross-regressive models, but in urban areas only. The effect of per pupil expenditures on migration to rural areas is not statistically significant. The incorporation of spatial regimes indicates that migration effects of per pupil expenditures certainly vary across the urban–rural spectrum and our results reveal interesting disparities with previous research focusing on the measurement of the impact of school quality on migration.

The paper is arranged as follows. Section 2 summarizes relevant studies that have examined the impact of school quality on migration patterns. Section 3 describes the typical migration model and extensions of spatial dependence. Section 4 describes the data sample and relevant variable characteristics. Section 5 provides a discussion of empirical results, and section 6 provides the conclusion.

2. Literature Review

A number of studies have examined the effect of government outlays for education on migration rate. Charney (1993) noted that educational services, provided by state and local governments as an investment in human capital, can either attract new capital or stimulate the outmigration of trained individuals. Cebula (1977) assumed that rapidly growing public education budgets imply stronger efforts to improve public education, though he did not examine the effect of expenditures on migration patterns directly. Quan and Beck (1987) found the effects of educational expenditures on the levels of wages and employment differ in the Northeast and Sunbelt but did not examine the effect expenditures on migration directly. Few studies (Cebula and Alexander; 2006; Cebula and Nair-Reichert, 2012) have used per pupil expenditures to understand the decision-making behavior of migrants. Early migration research used per capita public education outlays (Pack, 1973; Conway and Houtenville, 1998; Gale and Heath, 2000) perhaps due to availability of data.

There is reason to believe educational spending across counties is spatially dependent. Clustering of per pupil expenditures is evident across the midwestern and southern states, illustrating the possiblity of spillover effects across counties. It is therefore important to model this behavior, as characteristics of a county depend on its neighboring counties. Consumer-voters prefer to locate in areas comitted to greater financial resources toward primary and secondary public education (Cebula and Nair-Reichert, 2012), indicating that counties with higher per pupil expenditures possibly induce migration to those areas. Despite the awareness that spatial dependence exists, consideration of spatial effects across this literature is rare.

Cushing (1986) accounted for spatial relationships in four models of increasing complexity, the most complex of which accounts for adjacent states via a dummy variable which equals 1 if the origin and destination states are adjacent (Wall, 2001 measured contiguity as length of the border of contiguous regions times origin population). Cushing found that common borders and concentrations of origin populations near the border increase migration flows, giving reason for the consideration of spatial effects in migration models. Davies et al. (2001) later used distance to the destination state and distance squared as measures of spatial dependence (Jackman and Savouri, 1996 measured distance by number of highway miles in a study on migration in the UK). Rupasingha and Goetz (2004) estimated spatial dependence through the spatial lag and error terms (often labeled ARAR) for county-level inmigration data with focus on amenities, health factors and environmental conditions.

The traditional gravity model is used to describe international trade flows, migration and transportation, networks, and freight flows analysis and has been extended to include spatial dependence (Bolduc et al., 1992; Fischer and Griffith, 2008; LeSage and Pace; 2008). It is often estimated by least squares regression and includes variables that characterize origin and destination regions of flow and distance between the two. Fischer and Wang (2011) extend LeSage and Pace's (2008) spatial process model to include origin-based, destination-based and origin-to-destination based dependence.

In consideration of spatial effects, heterogeneity is as important as dependence. Urban and rural communities evolve differently and influence migration patterns in ways that have led to current depopulation trends of rural areas. This makes the use of spatial regimes appropriate for this study. Spatial regimes have been prevalent across different literature including regional development and epidemiological research (Yu and Wei, 2008; Sridharan et al., 2011; Chi and Marcouiller, 2012). The regime shift permits explanatory variables to vary over space (i.e. urban-rural spectrum), providing a way to combat spatial heterogeneity.

3. Model

The typical model used to describe interregional net or gross migration has the form

$$M_{ij} = [PC_i, LM_j, G_j, u_{ij}], \tag{1}$$

where M_{ij} refers to the migratory status of person i during the study period, PC_i refers to the socioeconomic characteristics of migrant i, LM_j refers to the labor market characteristics of area j, G_j refers to the geographical characteristics of area j, and u_{ij} is the stochastic error term. Socioeconomic characteristics that may exert influences on people's decisions to migrate could be age, level of education and race, for example. Labor market characteristics such as employment information and job opportunities are expected to increase with education, implying that both factors influence destination choice (Greenwood, 1975).

In this study we focus on the destination choice, which can be captured by inmigration rates. We study this choice by aggregating inmigration flows for each county, which is a modification of the micro-level model given in equation (1). The inmigration rate, given as the inmigration level divided by the destination population, is typically used since many dimensions of the benefits and costs of moving cannot be accounted for based on a simple flow. Therefore, population is used to convert migration to a more comprehensive measure of migration. While many have examined net migration, it is important to separate the effect of in- and out-migration (Sjaastad, 1962; Miller, 1973; Belanger and Rogers, 1992; Rogers and Henning, 1999), as net migration hides important underlying directional channels of migration flows.

Equation (1) is typically estimated by ordinary least squares (OLS), which is inappropriate in the presence of spatial dependence among regions. This is certainly true in the the case of gravity models since OLS assumes that (migration or other) flows are independent, an assumption that is invalid (Curry, 1972; Flowerdew and Aitkin, 1982; Griffith, 2007; LeSage and Pace, 2008; Fischer and Wang, 2011). Furthermore, the uneven size of regions may induce heteroskedasticity, which causes bias in the standard errors if estimated by OLS under standard Gauss-Markov assumptions.

Spatial dependence refers to dependence among outcomes at different locations and is often modeled in the form of a lagged dependent variable or in the disturbances. Spatial heterogeneity refers to differences among units being studied across locations in space (e.g., differences in house prices across spatial units of observation such as neighborhoods). Several papers in the hedonic house price literature (e.g., Brasington, 1999; Brasington and Hite, 2005) have addressed the issue of spatial effects and used spatial process models to account for instabilities across space and non-constant mean and/or variance of error terms.

We prefer the spatial Durbin model over the spatial lag model, as the latter is plausible only in the case of no omitted variables that are correlated with included explanatory variables, an assumption that is unlikely (LeSage and Fischer, 2008). Spatial dependence in the presence of omitted variables is thought to worsen the usual bias caused by estimating the data with OLS (LeSage and Pace, 2009). The spatial Durbin model, which includes spatial lags of the dependent and explanatory variables, has been found to "shrink the bias" relative to OLS in the case of omitted variables and spatial dependence in the error, dependent and explanatory variables (Pace and LeSage, 2010).

Meaningful variables are sometimes unavailable at different spatial levels, causing researchers to proxy for those variables as we have done. This leads us to believe that an omitted-variables problem in the context of county-level migration is likely. Furthermore, the spatial error model often prevents one from saying something meaningful regarding spatial dependence (though Glass et al., 2012, for example, provide support for the spatial error model over the spatial Durbin and lag models in the case of U.S. state vehicle useage). The spatial Durbin model contains spatially lagged dependent and explanatory variables:

$$y = \rho W y + X\beta + WZ\gamma + \epsilon, \epsilon \sim N(0, \sigma^2 I_n) \tag{2}$$

Spatial models permit relationships among sets of neighbors through an *n* x *n* weight matrix *W* that represents region *i*'s relationship to region *j*. The diagonal terms of *W* equal 0 by convention, as region *i* is not a neighbor of itself. The weight matrix is traditionally based on contiguity (queen or rook) or distance criterion (e.g. polygon centroids) (Anselin, 2002). Queen contiguity refers to neighbors along common boundaries and vertices while rook contiguity refers to neighbors along a common boundary of non-zero length. First order contiguous neighbors are regions with a common boundary and are defined as

$$w_{ij} = \begin{cases} 1 & \text{if region } j \text{ shares a common border with region } i \\ 0 & \text{otherwise.} \end{cases} \tag{3}$$

The weight matrix is row-standardized so the elements of each row sum to one; in a contiguity matrix, row-standardization implies that each neighbor of a region is given equal weight. In (2), ρ refers to the spatial autoregressive parameter that measures spatial dependence between the inmigration rates of U.S. counties and typically lies between –1 and 1. A positive value implies counties with high inmigration flows cluster together and counties with low inmigration flows cluster together, a negative value implies counties with high flows have neighbors with low flows, and 0 means complete spatial randomness.

The term Z may contain linearly independent columns of X, and WZ allows for spatially lagged explanatory variables. Several factors including unemployment rate are assumed to be transmitted across county borders, which, if not accounted for, leads to model misspecification (Anselin, 1988). School quality and demographic and socioeconomic characteristics also differ across space, and the term WX allows neighbor characteristics to spill over (Brasington and Hite, 2005).

The unidirectional Lagrange Multiplier (LM) tests are used to test for functional form misspecification. It is chosen over the Likelihood Ratio (LR) or Wald tests for its computational ease. The LM test is calculated for the spatial error (AR-error or SAR model), spatial lag and spatial ARAR model, which combines the error and lag models. A downside of unidirectional tests is that more than one type of autocorrelation may be present. To combat that issue, we test the error, lag, robust tests of both models and the ARAR model. We use the simple-to-complex approach to obtain the proper model specification (Anselin et al., 1996; Florax et al., 2003).

4. Data

The United States Census Bureau provides USA counties data files downloads compiled from various sources including previous years' Census, Bureau of Labor Statistics, National Center of Education Statistics and United States Department of Agriculture. The migration rate is calculated by the net number of inmigrants to county j over the period 2006-2010 as a percent of the 2006 population aged 20-49 in county j.We use beginning-of-period values for most explanatory variables except those for which we do not have data (we use general expenditures and per capita property taxes for 2002 and mean temperature for January for 1941-1970). Table 1 presents variables and descriptive statistics.

Table 1. Descriptive Statistics

Variable	*Description*	*Mean*		*Std.Dev.*		*Max*		*Min*	
Dependent =inflows		*Urban*	*Rural*	*Urban*	*Rural*	*Urban*	*Rural*	*Urban*	*Rural*
inflows	average annual inmigration flows, % of destination county population in 2006	0.089	0.079	0.039	0.047	0.460	0.456	0.017	0
avgppexp	average total per pupil expenditures	8490.966	8852.881	4039.075	2710.791	106272	55500	0	2693.667
arts	number of arts, recreation establishments, per 100,000 people	0.008	0.001	0.028	0.001	0.703	0.010	0	0
violcrime	# of violent crimes known to police, per 100,000 people	0.011	0.001	0.037	0.001	0.650	0.012	0	0
proptax	property tax per capita	781.419	766.264	458.237	653.976	5698	10747	0	27
medhousinc	median housing income	47921.519	36611.751	11863.003	6906.759	99934	100772	23404	16986
nonwhite	% nonwhite population	15.182	12.072	13.900	16.090	80	90.700	0.900	0.400
perownocc	owner-occupied housing units, % of total	72.111	73.805	9.075	6.509	92.500	89.900	21.600	29.800
popchng	% change in population 2000-2006	14907.105	453.223	43369.445	2610.986	703950	37692	-276126	-6587
empchng	% change in employment 2000-2006	9024.101	530.450	27494.724	1746.885	419207	20432	-143695	-5317
civunem	unemployed civilian labor force rate	4.583	5.072	1.396	1.797	15.400	14.200	0	1.600
housingest	housing unit estimates	94086.471	11781.903	189475.884	11287.628	3357428	112139	945	181
genexp	total Federal Government expenditure per capita	2858.707	2938.264	1206.739	1171.471	21506	12309	0.000	228
medyrsch	median years of schooling	15.376	14.189	3.240	3.449	18	18	9	9
tempjan	mean temperature in January 1941-1970	35.449	31.654	11.158	12.220	66.800	65.600	3.500	1.100
avgenroll	average school district enrollment	10949.173	1816.604	29052.019	2346.288	507062	25958	0	2

We examine the effect of primary and secondary school expenditures per pupil on the destination choice of migrants aged 20-49, as this age group is more likely to have school-age children than other age groups. Per pupil expenditures for 2006 were given for each school district in the U.S. These expenditures were averaged across each county to obtain an aggregate county measure. Average per pupil expenditures are larger in urban areas than in rural areas (Table 1).

The role of personal characteristics, such as age (Graves, 1979), education (Schwartz, 1973; Kodrzycki, 2001) and race, in migration literature is evident, as such characteristics significantly affect migration decisions (Cushing and Poot, 2004). Restriction on age has been used by others, including Greenwood (1988), who found that from their peak of about 25 years of age, migration rates decline steadily with age until about 65 years of age. Furthermore, the elderly may be less supportive of expenditures for education, especially those who have recently migrated and may lack a strong commitment to their new communities (Conway and Houtenville, 2001).

Other characteristics are likewise important for people's decisions to migrate. We use unemployment rate and median family income to describe labor market characteristics or economic opportunities (Graves, 1979; Greenwood and Hunt, 1989; Clark and Hunter, 1992). Several papers (i.e., Somers and Suits, 1973; Cebula, 1977) have preferred income over earnings in explaining migration patterns, as family income is considered a measure of not only the earnings per hour but also the number of hours/year that are worked, and the extent to which other family members can find work (Miller, 1973). However, Rayer and Brown (2001) found that median family income is not a statistically significant determinant of net migration. Among the relevant literature, there is further debate over the use of total income vs. per capita income, though the latter is a more appropriate measure of a nation's economic welfare (Romans, 1974).

Unemployment rate of the civilian population is often a deterent to inmigration (i.e., higher rates of unemployment are expected to have a decreasing effect on migration). We exclude military, as they may move around frequently and create bias with respect to the true inmigration rate. Areas with higher unemployment rates might be expected to experience more outmigration and less inmigration, though some have found that unemployment rates do not influence migration (Greenwood, 1975). Perhaps one would expect the presence of unemployment to motivate one to move to another locality in search of jobs; Lansing and Mueller (1967) concluded that unemployment rate encourages persons to move if they are young, well-educated, and trained.

Quality-of-life (QOL) characteristics, which include amenities (i.e., Graves and Linneman, 1979; Graves, 1983; Clark and Hunter, 1992; Conway and Houtenville, 1998) and disamenities, trigger shifts in migration patterns and have been considered important throughout the literature (Whisler et al., 2008). We use average, annual temperature in January and the existence of arts, entertainment and recreation establishments to account for quality of life. While some have found amenities to be important determinants of migration, that is, migrants move greater distances for higher amenities (Clark and Cosgrove, 1991; Clark and Hunter, 1992), some have found they are not (Greenwood and Hunt, 1989). Nevertheless, the importance of QOL characteristics in explaining migration has become more recognized over the years.

The cost of living index has been used by many over the years (Renas and Kumar, 1978; Alperovich, 1979; Cebula and Belton, 1994; Conway and Houtenville, 2001; Cebula and Alexander, 2006). The index has been used to explain migration under the notion that consumer-voters should not be subject to money illusion (i.e. consumer-voters should have a reasonable idea of what their net income will be given their expenses in the destination state) when evaluating the characteristics of potential destination states. Median housing value has been used to account for cost-of-living differences (Clark and Hunter; 1992). In addition to median housing value, we use population growth to capture cost-of-living differences between counties.

The concept of rurality has become important particularly in the context of migration, as the percentage of the U.S. population living in nonmetro areas has declined from 21 percent in 1990 to 16 percent today (USDA, ERS, 2013). Given this trend, we use spatial regimes to capture heterogeneity across urban and rural areas. The definition of urban/rural has changed over time, and researchers continue to use different measures (e.g., Isserman, 2005). We prefer the nonmetro/metro classification, which is defined on the basis of counties, our spatial unit of observation.

The Chow test gives an indication of heterogeneity, as it aids one in determining the appropriateness of pooling data across the urban/rural dichotomy. A significant Chow test statistic indicates that the sets of coefficients in two separate regressions are not equal (Table 2). This provides reason for incorporating a spatial regime in our model.

5. Results

We examine the effect of school quality on inmigration rate during the period 2006-2010 in the context of spatial processes. We follow Anselin et al. (1996) and find a significant, robust LM test for spatial lag (Table 2). This provides evidence for spatial dependence not only in the explanatory variables but also in the dependent variable, making the spatial Durbin model appropriate for this data. The cross-regressive model, which contains lagged explanatory variables, is estimated by ordinary least squares (Florax and Folmer, 1992), and the spatial Durbin model is estimated by maximum likelihood (ML). The ML estimator is chosen for its efficiency, and the spatial processes are estimated using the *spdep* package in *R* (Bivand, 2009). We reject the null hypothesis for homoskedasticity against the alternative for heteroskedasticity based on the Breusch-Pagan test statistics. We use the *lmtest* package provided by *R* to report heteroskedasticity-consistent standard errors.

We find the effect of average per pupil expenditures on inmigration is positively, statistically significant and consistent with others (Cebula and Alexander, 2006; Cebula and Nair-Reichert, 2012) given both models. The estimate for urban areas is more statistically significant than for rural areas. Table 2 provides results for the cross-regressive (CRM) and spatial Durbin (SDM) models. We turn our attention first to the cross-regressive model, which ex plains about 83 percent of the variation in county inmigration rate and contains direct (X) and indirect (WX) terms. The explanatory variables were rescaled by 100,000 and should be noted when interpreting the results.

The results imply a one-dollar increase in the variable of interest, per pupil expenditures, increases the inmigration rate by 1.81e-6 ((.151 + .030)/100,000), which is consistent with the traditional view that education services should promote migration (Tiebout, 1956). That estimate reflects urban areas, here defined as metropolitan counties. For rural areas, a one-dollar increase in per pupil expenditures increases the inmigration rate by 6.6e-7 ((.099 - .033)/100,000). While educational expenditures positively and significantly influence inmigration for both urban and rural areas, the effect is more statistically significant for urban areas. Furthermore, those impacts are not economically significant. In comparison, Cebula and Alexander (2006) found the impact of educational expenditures on migration rate was between .0039 and .0048. Cebula and Nair-Reichert (2012) found the impact was .00067. The effects are similar across the spatial Durbin model, though the estimate for urban areas is smaller (1.64e-6).

The divide between urban and rural areas is apparent across other variables. A one-dollar increase in median housing income increases the inmigration rate for urban areas by 8.3e-7 aggregate flows and for rural areas by 7e-7. An increase in the percent of owner-occupied housing decreases the inmigration rate for urban areas (.0027) by a larger amount than for rural areas (.0018). A one-dollar increase in housing estimates leads to a decline in urban inmigration by 4e-8 aggregate flows but does not statistically significantly affect rural inmigration. Crime is positively and statistically significant for only urban areas. This result is contrary to previous research, as crime is considered a disamenity. One reason for the discordant result is migrants to urban areas may feel more camaraderie to their neighbors, who have more civic responsibility to report crimes. The number of arts and recreation establishments likewise have differing effects across urban and rural areas. On the contrary, general expenditures per capita and average enrollment have similar effects in both regimes.

Table 2. Estimation Results

	b_{CRM} *Urban*	*s.e.*	b_{CRM} *Rural*	*s.e.*	b_{SDM} *Urban*	*s.e.*	b_{SDM} *Rural*	*s.e.*
constant	0.271***	0.044	0.163***	0.044	0.259***	0.043	0.153***	0.044
Wy					0.090**	0.029	0.090**	0.029
avgppexp	0.151***	0.036	0.099*	0.047	0.150***	0.035	0.098*	0.047
arts	0.128*	0.064	-2.658	2.908	0.133*	0.063	-2.465	2.916
violcrime	0.141*	0.064	-0.380	1.360	0.140*	0.064	-0.299	1.358
proptax	-0.337	0.746	-0.431	0.284	-0.347	0.735	-0.441	0.287
medhousinc	0.165***	0.030	0.035	0.031	0.165***	0.030	0.033	0.031
nonwhite	-11.866	20.815	3.209	17.728	-11.896	20.736	3.615	17.759
perownocc	-291.520***	36.391	-169.370***	23.455	-290.600***	36.460	-168.630***	23.404
popchng	-0.001	0.005	0.222***	0.066	-0.001	0.005	0.225***	0.066
empchng	0.008	0.007	0.057	0.077	0.008	0.007	0.051	0.076
civunem	0.002	0.003	-0.001	0.001	0.002	0.003	-0.001	0.001
housingest	-0.009***	0.002	-0.028	0.021	-0.009***	0.002	-0.029	0.021
genexp	-0.366*	0.183	-0.343*	0.136	-0.371*	0.183	-0.350**	0.136
medyrsch	13.793	32.356	25.364	30.630	12.650	32.195	24.910	30.600
tempjan	-33.392	78.578	164.750*	67.456	-33.764	78.326	166.900*	67.582
avgenroll	-0.018***	0.004	-0.280***	0.069	-0.018***	0.004	-0.276***	0.069
Wavgppexp	0.030	0.048	-0.033	0.106	0.014	0.049	-0.051	0.106
Warts	-0.595***	0.178	1.289	1.691	-0.595***	0.174	1.177	1.681
Wviolcrime	0.004	0.195	0.142	0.813	-0.018	0.192	0.053	0.811
Wproptax	-0.592	0.503	0.755	0.686	-0.536	0.499	0.779	0.685
Wmedhousinc	-0.082*	0.036	0.035	0.043	-0.091*	0.036	0.024	0.043
Wnonwhite	12.471	27.819	-15.907	22.498	11.724	27.690	-15.644	22.551
Wperownocc	18.935	46.060	-6.262	38.147	31.798	45.416	7.371	38.173
Wpopchng	0.004	0.012	-0.050	0.039	0.005	0.012	-0.049	0.039
Wempchng	0.033*	0.016	0.090	0.070	0.029	0.016	0.085	0.070
Wcivunem	-0.007*	0.003	0.000	0.002	-0.006*	0.003	0.000	0.002
Whousingest	0.005	0.004	-0.015	0.017	0.005	0.004	-0.011	0.017
Wgenexp	0.183	0.288	0.415	0.321	0.186	0.284	0.437	0.321
Wmedyrsch	-40.211	76.387	14.038	69.674	-38.126	76.035	11.398	69.499
Wtempjan	17.412	86.678	-110.540	73.920	14.739	86.304	-119.210	73.896
Wavgenroll	-0.004	0.011	-0.023	0.035	-0.002	0.011	-0.019	0.035
N	3076				3076			
Adjusted R^2	0.828				0.286			
Chow test	2.7918***							
Lagrange Multiplier test (error)	5.466*							
Lagrange Multiplier test (lag)	9.219**							
Robust LM (error)	6.168*							
Robust LM test (lag)	9.920**							
SARMA (error + lag)	15.386***							
Breusch-Pagan test	274.698***				273.793***			

Heteroskedasticity-consistent standard errors presented *** $p<.001$ ** $p<.01$ * $p<.05$
State fixed effects are included in both models

The autoregressive parameter, ρ, for the spatial Durbin model is positive (.090) and statistically significant, making the OLS estimates of the cross-regressive model biased. A positive ρ indicates that counties with high inmigration rates cluster together and counties with low inmigration rates cluster together. Coefficients of the cross-regressive and spatial Durbin models cannot readily be compared, as computation of marginal effects for the latter is more involved (LeSage and Pace, 2009). Based on (2), the N-by-N matrix of marginal effects is given as

$$\frac{\partial y}{\partial x_k} = (I - \rho W)^{-1}(\beta_k + W\gamma_k) + \epsilon \tag{4}$$

Table 3 provides the average indirect and direct impact measures for both models (note: marginal effects for the cross-regressive model are mathematically equivalent to the coefficients). The direct impacts for rural and urban areas have the same sign and approximately the same magnitude across the cross-regressive and spatial Durbin models. We expect this, as the direct impacts correspond to the base model with lagged explanatory variables, whose effects reach only the local neighbors and not the whole spatial system. A one-dollar increase in average per pupil expenditures, for example, increases urban inmigration by 1.5e-6 and rural inmigration by 9.9e-7 aggregate flows. The gap between urban and rural effects is bridged slightly by the spatial Durbin model, though the statistical significance of the direct effects for urban and rural areas remain the same as in Table 2.

The indirect effects, which involve the lagged dependent variable, spread to the whole spatial system and affect the rural areas, in particular, differently for per pupil expenditures. We notice the indirect effect of school expenditures on rural inmigration is negative for the cross-regressive model but positive for the spatial Durbin model. Nevertheless, the overall outcome, whereby the total effect on urban inmigration is 1.65e-6 and on rural inmigration is 1.09e-6, suggests a similar result to that obtained from Table 2.

Table 3. Impact Measures

	$Direct_{CRM}$		$Indirect$		$Direct_{SDM}$		$Indirect$	
	$Urban$	$Rural$	$Urban$	$Rural$	$Urban$	$Rural$	$Urban$	$Rural$
avgppexp	0.151***	0.099*	0.030	-0.033	0.150***	0.099*	0.015*	0.010
	(0.036)	(0.047)	(0.048)	(0.106)	(0.002)	(0.002)	(0.000)	(0.000)
arts	0.128*	-2.658	-0.595***	1.289	0.133	-2.469	0.013	-0.239
	(0.064)	(2.908)	(0.178)	(1.691)	(0.004)	(0.120)	(0.000)	(0.013)
violcrime	0.141*	-0.380	0.004	0.142	0.140	-0.300	0.014	-0.029
	(0.064)	(1.360)	(0.195)	(0.813)	(0.004)	(0.055)	(0.000)	(0.006)
proptax	-0.337	-0.431	-0.592	0.755	-0.347	-0.441*	-0.034	-0.043
	(0.746)	(0.284)	(0.503)	(0.686)	(0.020)	(0.009)	(0.002)	(0.001)
medhousinc	0.165***	0.035	-0.082*	0.035	0.166***	0.033	0.016**	0.003
	(0.030)	(0.031)	(0.036)	(0.043)	(0.001)	(0.001)	(0.000)	(0.000)
nonwhite	-11.866	3.209	12.471	-15.907	-11.913	3.620	-1.155	0.351
	(20.815)	(17.728)	(27.819)	(22.498)	(0.724)	(0.552)	(0.075)	(0.057)
perownocc	-291.520***	-169.370***	18.935	-6.262	-291.007***	-168.866***	-28.211**	-16.370**
	(36.391)	(23.455)	(46.060)	(38.147)	(0.950)	(0.759)	(0.476)	(0.280)
popchng	-0.001	0.222***	0.004	-0.050	-0.001	0.225***	0.000	0.022*
	(0.005)	(0.066)	(0.012)	(0.039)	(0.000)	(0.003)	(0.000)	(0.000)
empchng	0.008	0.057	0.033*	0.090	0.008	0.051	0.001	0.005
	(0.007)	(0.077)	(0.016)	(0.070)	(0.000)	(0.004)	(0.000)	(0.000)
civunem	0.002	-0.001	-0.007*	0.000	0.002	-0.001	0.000	0.000
	(0.003)	(0.001)	(0.003)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)
housingest	-0.009***	-0.028	0.005	-0.015***	-0.009	-0.029*	-0.001	-0.003
	(0.002)	(0.021)	(0.004)	(0.017)	(0.000)	(0.001)	(0.000)	(0.000)
genexp	-0.366*	-0.343*	0.183	0.415	-0.371**	-0.350**	-0.036	-0.034*
	(0.183)	(0.136)	(0.288)	(0.321)	(0.006)	(0.005)	(0.001)	(0.001)
medyrsch	13.793	25.364	-40.211	14.038	12.668	24.945	1.228	2.418
	(32.356)	(30.630)	(76.387)	(69.674)	(1.836)	(1.167)	(0.195)	(0.128)
tempjan	-33.392	164.750*	17.412	-110.540	-33.812	167.132**	-3.278	16.202
	(78.578)	(67.456)	(86.678)	(73.920)	(4.275)	(2.504)	(0.434)	(0.361)
avgenroll	-0.018***	-0.280***	-0.004	-0.023	-0.018**	-0.276***	-0.002*	-0.027*
	(0.004)	(0.069)	(0.011)	(0.035)	(0.000)	(0.003)	(0.000)	(0.001)

SDM impact measures are calculated using bootstrap procedure in *spdep* package
Standard errors are reported in parentheses *** p<.001 ** p<.01 * p<.05

6. Conclusion

This analysis examines the effect of school quality, measured by per pupil expenditures, on inmigration rate given spatial process models. Migration literature on the adapation of processes to account for spatial dependence and heterogeneity is sparse. We examine the cross-regressive and spatial Durbin models to bridge the gap between traditional migration methods and spatial processes in the gravity-type framework. Furthermore, we use spatial regimes to account for heterogeneity across rural and urban areas, which has become a phenomenon of late given depopulation trends across rural areas.

The results differ from most prior research that has analyzed fiscal determinants of migration. One reason is the treatment of regions as independent, a notion that is incorrect and should be corrected by spatial processes. Another reason is the analysis of educational spending on aggregate rather than disaggregated areas. We find that while per pupil expenditures have a positive and significant effect on urban and rural in-migration, the effect on urban areas is more statistically significant. Once we take impact measures into account, we find the effects of expenditures are further lessened, as only the direct, and not indirect, impacts are statistically significant across both models.

References

Alperovich, Gershon. "The cost of living, labor market opportunities and the migration decision: A case of misspecification?: Comment." The Annals of Regional Science 13.3 (1979): 102-105.

Anselin, Luc. Spatial econometrics: methods and models. Vol. 4. Kluwer Academic Pub, 1988.

——— "Under the hood issues in the specification and interpretation of spatial regression models." Agricultural economics 27.3 (2002): 247-267.

Anselin, Luc, et al. "Simple diagnostic tests for spatial dependence." Regional science and urban economics 26.1 (1996): 77-104.

Belanger, Alain, and Andrei Rogers. "The internal migration and spatial redistribution of the foreign-born population in the United States: 1965-70 and 1975-80." International Migration Review (1992): 1342-1369.

Bivand, Roger. "spdep: Spatial Dependence: Weighting Schemes, Statistics and Models," http://cran.r-product.org/web/packages/spdep/spdep.pdf. (2009)

Bolduc, Denis, Richard Laferriere, and Gino Santarossa. "Spatial autoregressive error components in travel flow models." Regional Science and Urban Economics 22.3 (1992): 371-385.

Brasington, David M. "Which measures of school quality does the housing market value?." Journal of real estate research 18.3 (1999): 395-413.

Brasington, David M., and Diane Hite. "Demand for environmental quality: a spatial hedonic analysis." Regional science and urban economics 35.1 (2005): 57-82.

Cebula, Richard J. "An analysis of migration patterns and local government policy toward public education in the United States." Public Choice 32.1 (1977): 113-121.

Cebula, Richard J., and Gigi M. Alexander. "Determinants of net interstate migration, 2000-2004." Journal of Regional Analysis and Policy 36.2 (2006): 116-123.

Cebula, Richard J., and Willie J. Belton. "Voting with one's feet." American Journal of Economics and Sociology 53.3 (1994): 273-280.

Cebula, Richard J., and Usha Nair-Reichert. "Migration and public policies: a further empirical analysis." Journal of Economics and Finance 36.1 (2012): 238-248.

Charney, Alberta H. "Migration and the public sector: a survey." Regional Studies 27.4 (1993): 313-326.

Chi, G. and D.W. Marcouiller. 2012. Natural amenities and their effects on migration along the urban-rural continuum. Annals of Regional Science. Online DOI 10.1007/s00168-012-05424-2

Clark, David E., and James C. Cosgrove. "Amenities versus labor market opportunities: Choosing the optimal distance to move." Journal of Regional Science 31.3 (1991): 311-328.

Clark, David E., and William J. Hunter. "The impact of economic opportunity, amenities and fiscal factors on age-specific migration rates." Journal of Regional Science 32.3 (1992): 349-365.

Conway, Karen Schmith, and Andrew J. Houtenville. "Do the elderly vote with their feet?." Public Choice 97.4 (1998): 663-685.

——— "Elderly migration and state fiscal policy: evidence from the 1990 census migration flows." National Tax Journal 54.1 (2001): 103-123.

Curry, Leslie. ”A spatial analysis of gravity flows.” Regional Studies 6.2 (1972): 131-147.

Cushing, Brian J. ”Accounting for spatial relationships in models of interstate population migration.” The Annals of Regional Science 20.2 (1986): 66-73.

Cushing, Brian, and Jacques Poot. ”Crossing boundaries and borders: Regional science advances in migration modelling.” Papers in Regional Science 83.1 (2003): 317-338.

Davies, Paul S., Michael J. Greenwood, and Haizheng Li. ”A conditional logit approach to US state-to-state migration.” Journal of Regional Science 41.2 (2001): 337-360.

Fischer, Manfred M., and Daniel A. Griffith. ”Modeling spatial autocorrelation in spatial interaction data: An application to patent citation data in the European Union.” Journal of Regional Science 48.5 (2008): 969-989.

Fischer, Manfred M. and Jinfeng Wang. Spatial Data Analysis Models, Methods and Techniques. Springer Briefs in Regional Science. 2011.

Florax, Raymond, and Henk Folmer. ”Specification and estimation of spatial linear regression models: Monte Carlo evaluation of pre-test estimators.” Regional Science and Urban Economics 22.3 (1992): 405-432.

Florax, Folmer and Rey Specification Searches in Spatial Econometrics: The Relevance of Hendrys Methodology, Regional Science and Urban Economics 33(5), 2003, 557–79.

Flowerdew, Robin, and Murray Aitkin. ”A method of fitting the gravity model based on the Poisson distribution.” Journal of Regional Science 22.2 (1982): 191-202.

Folger, John K., and Charles B. Nam. Education of the American population. Arno Press, 1976.

Gale, Lewis R., and Will Carrington Heath. ”Elderly internal migration in the United States revisited.” Public Finance Review 28.2 (2000): 153-170.

Glass, Anthony J., Karligash Kenjegalieva, and Robin C. Sickles. ”How efficiently do US cities manage roadway congestion?.” Journal of Productivity Analysis (2012): 1-22.

Graves, Philip E. ”A Life-Cycle Empirical Analysis of Migration and Climate, by Race (JUE 1979).” Journal of Urban Economics 6 (1979): 135-147.

——— ”Migration with a composite amenity: The role of rents.” Journal of Regional Science 23.4 (1983): 541-546.

Graves, Philip E., and Peter D. Linneman. ”Household migration: Theoretical and empirical results.” Journal of urban economics 6.3 (1979): 383-404.

Greenwood, Michael J. ”An analysis of the determinants of geographic labor mobility in the United States.” The Review of Economics and Statistics 51.2 (1969): 189-194.

——— ”Research on internal migration in the United States: a survey.” Journal of Economic Literature 13.2 (1975): 397-433.

——— ”Changing patterns of migration and regional economic growth in the US: a demographic perspective.” Growth and Change 19.4 (1988): 68-86.

Greenwood, Michael J., and Gary L. Hunt. ”Jobs versus amenities in the analysis of metropolitan migration.” Journal of Urban Economics 25.1 (1989): 1-16.

Griffith, Daniel A. ”Spatial structure and spatial interaction: 25 years later.” The Review of Regional Studies 37.1 (2007): 28-38.

Harris, Amy Rehder, William N. Evans, and Robert M. Schwab. ”Education spending in an aging America.” Journal of Public Economics 81.3 (2001): 449-472.

Isserman, Andrew M. ”In the national interest: Defining rural and urban correctly in research and public policy.” International Regional Science Review 28.4 (2005): 465-499.

Jackman, Richard, and S. Savouri. Regional migration and the hiring function: an examination of distance and contiguity effects in Great Britain: 1975-92. Routledge, 1996.

Kodrzycki, Yolanda K. ”Migration of recent college graduates: evidence from the national longitudinal survey of youth.” New England Economic Review (2001): 13-34.

Lansing, John. ”B. and E. Mueller. 1967.” The Geographic Mobility of Labor.

LeSage, James P., and Manfred M. Fischer. ”Spatial growth regressions: model specification, estimation and interpretation.” Spatial Economic Analysis 3.3 (2008): 275-304.

LeSage, James P., and R. Kelley Pace. ”Spatial econometric modeling of origin-destination flows.” Journal of Regional Science 48.5 (2008): 941-967.

Liu, Ben-Chieh. ”Local Government Finance and Metropolitan Employment Growth, a Simultaneous: Equation Model.” Southern Economic Journal (1977): 1379-1385.

Miller, Edward. ”Is out-migration affected by economic conditions?.” Southern Economic Journal (1973): 396-405.

Navratil, Frank J., and James J. Doyle. ”The socioeconomic determinants of migration and the level of aggregation.” Southern Economic Journal (1977): 1547-1559.

Pace, R. Kelley, and J. P. LeSage. ”Introduction to spatial econometrics.” (2009).

——— ”Omitted variable biases of OLS and spatial lag models.” Progress in Spatial Analysis. Springer Berlin Heidelberg, 2010. 17-28.

Pack, Janet Rothenberg. ”Determinants of migration to central cities.” Journal of Regional Science 13.2 (1973): 249-260.

Quan, Nguyen T., and John H. Beck. ”Public education expenditures and state economic growth: Northeast and Sunbelt regions.” Southern Economic Journal (1987): 361-376.

Rayer, Stefan, and David L. Brown. ”Geographic diversity of inter-county migration in the United States, 19801995.” Population Research and Policy Review 20.3 (2001): 229-252.

Renas, Stephen M., and Rishi Kumar. ”The cost of living, labor market opportunities, and the migration decision: A case of misspecification?.” The Annals of Regional Science 12.2 (1978): 95-104.

Rogers, Andrei, and Sabine Henning. ”The internal migration patterns of the foreign-born and native-born populations in the United States: 1975-80 and 1985-90.” International Migration Review (1999): 403-429.

Romans, J. Thomas. ”Benefits and burdens of migration (with specific references to the brain drain).” Southern Economic Journal (1974): 447-455.

Rupasingha, Anil, and Stephan J. Goetz. ”County amenities and net migration.” Agricultural and Resource Economics Review 33.2 (2004): 245-254.

Saltz, Ira S. ”State income tax policy and geographic labour force mobility in the United States.” Applied Economics Letters 5.10 (1998): 599-601.

Schmidt, Lucie, and Paul N. Courant. ”Sometimes close is good enough: The value of nearby environmental amenities.” Journal of Regional Science 46.5 (2006): 931-951.

Schwartz, Aba. ”Interpreting the effect of distance on migration.” The Journal of Political Economy (1973): 1153-1169.

Sjaastad, Larry A. ”The costs and returns of human migration.” The journal of political economy 70.5 (1962): 80-93.

Sridharan, Sanjeev, Julia Koschinsky, and Jeremy J. Walker. ”Does context matter for the relationship between deprivation and all-cause mortality? The West vs. the rest of Scotland.” International journal of health geographics 10.1 (2011): 33-46.

Sommers, Paul M., and Daniel B. Suits. ”Analysis of net interstate migration.” Southern Economic Journal (1973): 193-201.

Tiebout, Charles M. ”A pure theory of local expenditures.” The journal of political economy 64.5 (1956): 416-424.

Tobler, W. R. ”Cellular geography.” Philosophy in geography. Springer Netherlands, 1979. 379-386.

USDA ERS (2004) Measuring rurality: Rural-urban continuum codes. Washington, D.C.: Economic Research Service, USDA

Wall, Howard J. ”Voting with your feet in the United Kingdom: Using cross-migration rates to estimate relative living standards.” Papers in Regional Science 80.1 (2001): 1-23.

Whisler, Ronald L., et al. ”Quality of Life and the Migration of the College Educated: A Life-Course Approach.” Growth and Change 39.1 (2008): 58-94.

Yu, Danlin, and Yehua Dennis Wei. ”Spatial data analysis of regional development in Greater Beijing, China, in a GIS environment*.” Papers in Regional Science 87.1 (2008): 97-117.