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Filling the Gaps: Explanations for Disparities in the Distribution of Dentists among U.S. Counties

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Abstract: This study identifies determinants of the geographic distribution of U.S. dentists. Significant and growing disparities exist among counties in the number of dentists per capita, which have potential ramifications for resident health and economic vitality for underserved areas. This study examines the geographic distribution of dentists using a utility maximizing model of dental location and spatial econometric methods. Results indicate that demand factors such as income, private insurance, education, and age affect dentist disparities. Also, dentists cluster in counties with urban areas of at least 10,000 residents, higher net in-commuting, greater proportions of creative class professionals, and dental schools. Spatial econometric models improve fit over spatially naïve models and provide evidence of spatial dependencies. Results suggest that some county disparities are immutable and that dentist recruitment and retention efforts should be linked with community, workforce, and economic development plans in collaboration with other localities in the region.

1. Introduction

This paper examines regional disparities of dentists in the United States. This issue is important for several reasons. First, significant disparities in dental care access exist and the number of underserved areas is growing. For instance, areas designated as Dental Health Professional Shortage Areas (dHPSAs) have more than doubled from December 2001 to July 2011 from 1,853 to 4,661 with concomitant increases in the underserved population from 38.5 million to 52 million. Second, dentist availability influences resident oral healthcare access and utilization, which can affect resident oral and overall physical health, productivity, and quality of life. It may also form part of a bundle of local characteristics with amenity value that influences the location choices of migrants. Third, dentists are a small but important part of the local economies of small towns and rural areas throughout the U.S. As with other health care professionals, the attrition or loss of local dentists and associated leakage of dollars could have a negative impact on local economies (Doeksen et al, 1998). Fourth, growing dentist disparity changes have occurred despite public policies and significant public resources invested over several decades in improving oral health care access and dentist diffusion, including the construction of public and non-profit private dental clinics, expansion of public health insurance programs with dental components such as Medicaid, and establishment of dentist scholarships and location subsidies to influence dental practice location choices.

Health workforce to population ratios are a popular measure of health service access disparities. They are simple to convey but have sometimes been criticized for providing a misleading gauge of workforce inadequacies (Wade and House, 2008; Rosenthal, Zaslavsky and Newhouse, 2005; Hong and Kindig, 1992; Newhouse et al., 1982). Defining inadequacy by population ratio implicitly assumes that the only determinant of need is the size of the resident population. But the need for dental professionals in an area only has meaning in relation to the services that would actually be purchased if the services were available, in other words, the demand for the services. Moreover, the amount of services available in an area also depends on the willingness of providers to locate there, in other words, the supply of services. To know whether the supply of dentists is adequate, we need to know the demand for the services; to know what to do about a perceived inadequacy, we need to know what is limiting the supply. If identifiable demand and supply factors are responsible for the disparities in dentist distribution, policymakers may have more success trying to alter these underlying regional demand and supply characteristics than, say, simply attempting to increase the supply of providers through mechanisms such as temporary locational financial incentives.

Many studies of the geographical distribution of dentists have made only limited efforts to identify demand and supply drivers (Saman, Arevalo, and Johnson, 2010; Wall and Brown, 2007; Krause, Frate, and May, 2005; Nainar and Feigal, 2004; Mertz and Grumbac, 2001; Lowell-Smith, 1993). They have also generally restricted their attention to localities within one state or states within the nation, making broader generalizations about geographical patterns difficult. Despite the obvious relevance of space in modeling geographical dental profession service levels, spatial factors and spatial econometric modeling have also received little attention in this literature.

This paper attempts to address these gaps by describing a utility location model incorporating multiple demand and supply factors, increasing the geographic scope to include all counties in the continental United States, and utilizing spatial econometric methods to account for unexplained sources of heterogeneity and describe spatial spillover processes. We believe that a greater understanding of dentist spatial location patterns can be obtained that better informs policy by identifying mutable and immutable characteristics of areas that affect dentist location.

This paper is divided into several sections. The first section reviews the economic and public health literature on the determinants of dentist location. The second section describes the methodology and data. The third section presents the model estimation results. The fourth section discusses policy implications of the analysis. The final section contains a summary and conclusion.

2. Literature review

In a market-driven system, where dentists choose to settle depends in large part on the opportunities to operate a profitable practice and hence on the income and population characteristics of the region as well as the number and characteristics of competing providers of services in the region. Also, consumption opportunities and non-consumptive good availability such as natural amenities and public goods may be important. The starting point for this discussion is a stylized model of the health care professional location decision along the lines of Goetz and Debertin (1996) and Olfert et al. (2012) in which a representative dentist selects a location based on maximizing utility among competing j jurisdictions over a set of composite goods (Z), area amenities (A_j), and government services (G_j).[1] The dentist maximizes a utility described by:

$$U = U(Z, A_j, G_j) \tag{1}$$

This utility is constrained by a budget characterized as:

$$Pz_j Z = Y_j - T_j \tag{2}$$

where Pz_j is the price of the composite good which varies by area, T_j is jurisdiction taxes, and Y_j is income potential. (1) and (2) can be combined to produce an indirect utility function:

$$V_j = V(Y_j, Pz_j, T_j, A_j, G_j) \tag{3}$$

Thus, the drawing power of a location for dentists will depend on area amenities, public goods costs and provision, and income potential. Income potential will vary based on area consumer demand characteristics and the dental market characteristics of proximate jurisdictions. Features of consumer demand considered here include area population, economic characteristics reflecting resident dental services purchasing power such as health insurance and income, resident dental care preferences and oral health status, and geographical location variables capturing transportation access costs. Each of these variable categories is discussed in further detail below.

Dental insurance and income are key consumer demand factors. By reducing the cost of care, dental insurance significantly increases the likelihood of

[1] A summary of such services and their varied impacts can be found in Cebula (1979).

visiting a dentist (Manski and Brown, 2007) as well as the number of visits and level of expenditures (Manski, Macek, and Moeller, 2002). Furthermore, when one compares families without dental insurance at various income levels, those with higher incomes are more likely to report a dental visit (Manski, Macek, and Moeller, 2002).

People vary also in their tastes and preferences for good oral health. Educational achievement affects awareness of dental care benefits and makes it possible to lower the costs of obtaining dental care. Studies find lower perceived need for care in rural areas and among individuals with low socioeconomic status, which may be due to the social environment and expectations for good teeth (Martin et al., 2008). Age also plays a role. The elderly tend to have lower utilization rates because they have lower expectations of good oral health as they age (Kiyak and Reichmuth, 2005). On the other hand, seniors have the highest average annual expense among all age groups (Institute of Medicine, National Research Council, 2011), reflecting the need for much costlier dental services when care is in fact actually obtained.

Time spent traveling to care and waiting on service may also reduce dental services utilization. The empirical evidence on the importance of these time costs is inconclusive (Sintonen and Linnosmaa, 2000). Measuring the effects is complicated by the fact that individuals often bundle their purchases of dental services with other goods and services and that provider prices vary in response to expected wait times (Wade and House, 2008). Travel time costs also vary among regions because of differences in the opportunity costs of time. Wages, which are a measure of the opportunity cost of visiting a provider during working hours, tend to be lower in rural areas. As a result the cost of the extra travel time is at least partially offset by the lower opportunity cost of time.

Supply factors are also potentially important determinants of dentist location. For instance, the availability of local amenities influences migration flows. Natural amenities such as climate and features of the natural landscape (e.g., lakes, coastlines, mountains) are usually emphasized (Graves, 1980; McGranahan, 1999; Cebula and Alexander, 2006). More recent work surrounds aspects of the built environment such as historical buildings, bike paths, and parks and cultural and entertainment amenities like restaurants, bookstores, art galleries, and museums. Amenities are thought to be especially important for members of the so-called creative class, workers in knowledge fields and the professions, who have more independence in their locational choices (Florida, 2002). Numerous studies call attention to the fact that dentists and other health care professions favor more urbanized locations and are willing to trade off urban amenities for income or may be willing to "induce demand" for their services in their preferred location (Dussault and Franceschini, 2006; Goetz and Debertin, 1996; Cromwell and Mitchell, 1986).

State and local government taxation has a direct effect on after-tax income and should also affect dentist locational choices. Evidence suggests that property taxes and income taxes generally decrease in-migration (Fox, Herzog, and Schlottman, 1989). How the revenue is used also matters. Higher expenditures on primary and secondary education produce amenity value that attracts in-migrants (Fox, Herzog, and Schlottman, 1989). Members of the professions may be expected to place an even higher premium on such education quality. However, in the few instances that tax and fiscal variables have been used to model health care profession distribution, the results have been varied (Mistretta, 2007; Carpenter and Neun, 1999; Goetz and Debertin, 1996).

A strong case can be made also for the role of space and spatial dependencies in the geographic distribution of dentists and other health professionals. Central Place Theory holds that there is a certain geographical structure to service markets and that as a place grows in size, the range of goods and services (including health care services) provided increases. Moreover, health care professions might be expected to cluster because of agglomerative forces such as shared customers or inputs. The demand and supply characteristics of one area can be expected to affect the demand and supply of nearby areas. A relatively high number of dentists in one region might induce lower levels in a nearby region because of "border crossing," while favorable consumer demand conditions in one region might similarly attract providers to adjacent regions.

Despite the obvious relevance of space in modeling geographical dental profession service levels, spatial factors have received little attention in the literature. The wider literature on health profession distribution seems also to have generally overlooked the importance of spatial variables and the need for spatial econometric modeling. It is not that researchers have ignored the spatial dimension altogether, but rather that they have rarely been formally introduced into empirical models of health profession distribution. For example, Newhouse et al. (1982) examine the relationship between urban hierarchy and prevalence of physician specialists. Wade and House (2008) and Hong and Kindig (1992) describe how travel and commuting patterns affect the location of dental services but never formally test the relationship.

3. Data and methods

We estimate the reduced-form model of dentist location/distribution suggested by equation (3) in section 2. Similar reduced form models to estimate the influence of demand and supply factors on health care profession distribution have been motivated by slightly different analytical frameworks (Carpenter and Neun, 1999; Beazoglou et al., 1992). Moreover, a larger regional science literature has examined the determinants of internal migration using reduced form equations based on household utility maximizing or human capital investment models that often identify similar types of explanatory variables (Cebula and Alexander, 2006; Cushing and Poot, 2004; Greenwood, 1985). These models differ in that they examine the flow of population rather than the stock of workers and usually represent the income potential available at alternative locations for a generic worker by average income and employment opportunity measures such as average wages, unemployment rates, and employment growth rates.

The dependent variable is the number of professionally active dentists per 100,000 residents in 2007. Professionally active dentists may work in private practice or in the public and non-profit sectors and also include dental school faculty/staff as well as military dentists. Table 1 describes each variable in the model and its corresponding data source. The geographical units of analysis are counties and county equivalents (e.g., independent cities in some states, parishes in Louisiana) in the contiguous U.S. states.

Consumer demand for dental services is represented by several variables. We use per capita nominal income (*INC*) to reflect the finding that demand for dental services increases with income (Beazoglou et al., 1992). Data on the prevalence of dental insurance at a local level was unavailable. Therefore, a proxy variable, the percentage of the population with health insurance (*PINSURE*), was used instead. Varied preferences for dental services and oral health status are represented by the percentage of the population with a college degree (*PCOLL*), percentage of the population 65 years and older (*PSENIOR*) and percentage of the population that is of a race/ethnicity category other than non-Hispanic white (*PMIN*). Three variables reflect differential transportation costs of accessing dental services (*AREA*, *HIGHWAY*, and *NETCOM*). Higher transportation costs will reduce the quantity demanded of dental services. Transportation costs should be lower for smaller counties (Beazoglou et al., 1992) and counties served by Interstate highways. Higher levels of net commuting should increase the demand for local dental services because workers are more likely to utilize dental services near their workplaces (Hong and Kindig, 1992).

We use several supply-related variables. Natural amenities (*AMENITY*) include climate characteristics and features of the natural landscape (e.g., lakes, mountains). This variable is a county level score based on temperature, humidity, topography, and water area components (McGranahan, 1999). A creative class variable (*CREATIVE*) measures the percentage of county employment in creative class occupations defined as those requiring a relatively high level of advanced development, design, or analytical skills (McGranahan and Wojan, 2007). State and local government fiscal variables affect income and amenity level indirectly. *Ceteris paribus*, state and local taxes (*TAXES*) hinder entry while higher spending on educational amenities (*EDSPEND*) makes an area more attractive (Cebula, 1979; Cebula and Alexander, 2006).

Geographical clustering may occur in health care services. Clustering may occur because of central place theory, the tendency of higher order services to be offered at more centralized locations. These services may also cluster because dental services can be produced at lower cost in certain areas due to localization and urbanization economies in the health care sector. Urbanization economies are represented by the presence of county urbanization that reaches various population size thresholds (*CITY10, CITY25, CITY100, CITY250, CITY500,* and *CITY1000*).

One additional supply variable (*SCHOOL*) is included to measure the presence of an accredited dental school in the county. This variable is surmised to boost the number of local dentists.

Table 1. Variable definitions and data sources.

Variable	Definition	Data Source
ACTIVE	Number of professionally active dentists per 100,000 residents	Health Resources and Services Administration, Area Resource File, 2009-2010 and National Cancer Institute, Surveillance Epidemiology and End Results (SEER)
INC	Per capita income in 2009 inflation adjusted dollars (in thousands)	U.S. Census Bureau, American Community Survey, 2005-2009
PINSURE	Percentage of population under 65 years of age with health insurance	U.S. Census Bureau, Small Area Health Insurance Estimates (SAHIE), 2007
PCOLLEGE	Percentage of population 25 years and older with college education	U.S. Census Bureau, American Community Survey, 2005-2009
PMIN	Percentage of population that is non-white or Hispanic	U.S. Census Bureau, American Community Survey, 2005-2009
PSENIOR	Percentage of population 65 years or older	U.S. Census Bureau, American Community Survey, 2005-2009
AREA	Land area in square miles	U.S. Census Bureau, County and City Data Book, 2007
HIGWAY	Dummy variable indicating Interstate highway mileage greater than zero	Bureau of Transportation Statistics, National Transportation Atlas Database, National Highway Planning Network, 2010
NETCOM	Net commuting (incommuters-outcommuters) as a percentage of population, 2000	U.S. Census Bureau, Census 2000, County-to-County Worker Flow Files
CITY10	Dummy indicating urban population of at least 10,000	U.S. Census Bureau, 2000
CITY25	Dummy indicating urban population of at least 25,000	U.S. Census Bureau , 2000
CITY100	Dummy indicating urban population of at least 100,000	U.S. Census Bureau, 2000
CITY250	Dummy indicating urban population at least 250,000	U.S. Census Bureau, 2000
CITY500	Dummy indicating urban population at least 500,000	U.S. Census Bureau, 2000
CITY1000	Dummy indicating urban population at least 1,000,000	U.S. Census Bureau, 2000
AMENITY	Natural amenities scale	U.S. Department of Agriculture, Economic Research Service, Natural Amenities Scale
CREATIVE	Creative class share of employment, 2000	U.S. Department of Agriculture, Economic Research Service, Creative Class County Codes
EDSPEND	State and local primary and secondary education spending per capita	U.S. Census Bureau, 2007 Census of Governments
TAXES	State and local property, sales, and income taxes per capita	U.S. Census Bureau, 2007 Census of Governments
SCHOOL	Dummy indicating dental school located in county	American Dental Association (2010)

We compare several spatial econometric models described by LeSage and Pace (2009) in order to select the most appropriate model. Comparisons are made among a baseline Ordinary Least Squares (OLS) (equation 5) and three types of spatial regression models: the Spatial Autoregressive Model (SAR) (equation 6), the Spatial Error Model (SEM) (equation 7), and the Spatial Durbin Model (SDM) (equation 8). The stochastic error terms are normally distributed.

$$y = X\beta + \epsilon \tag{5}$$

$$y = \rho Wy + X\beta + \epsilon \tag{6}$$

$$y = X\beta + u \tag{7}$$
$$u = \lambda Wu + v$$

$$y = \rho Wy + X\beta + \theta WX + \epsilon \tag{8}$$

$$\epsilon \sim N(0, \sigma^2 I_n) \qquad u \sim N(0, \sigma^2 I_n) \tag{9}$$

Each of these spatial models has a slightly different motivation as explained in LeSage and Pace (2009). The SAR is motivated by a belief that the dependent variable is spatially autocorrelated. This situation occurs if dentist density is systematically associated with higher or lower dentist densities in nearby counties. The SEM model is motivated by the belief that that the error term is spatially autocorrelated. This situation occurs if the model omits variables from the specification that are correlated over space. For example, there may be oral health status variables reflecting regional tastes and preferences that are not included in the model. The SDM model is motivated by the belief that omitted independent variables are correlated over space and also correlated with a model independent variable. For example, Appalachian region residents may exhibit similar tastes and preferences for oral health and Appalachian residency could be highly correlated with included independent variables such as natural landscape features (incorporated into the *AMENITY* measure) or socioeconomic status variables. In addition to theoretical motivations, formal tests among the competing models can be conducted. LeSage and Pace show that OLS, SAR, and SEM are nested within SDM and that SDM will produce unbiased estimators. Log likelihoods can be used to choose among the competing models.

LeSage and Pace caution against comparing coefficient estimates from the SDM with OLS coefficient estimates. Individual elements of the β coefficient vector can be interpreted as the marginal effect of a unit change in the corresponding element of the design matrix X. In contrast, SDM coefficient estimates, like other models incorporating a lagged dependent variable (e.g., SAR, Spatial Autocorrelation Model (SAC), Spatial Autoregressive Moving Average Model or SARMA), require a different interpretation. For the SDM model, variation in dentists per capita is related to the concentration of dentists in nearby counties, represented by the spatial lag term, Wy, in addition to the values of independent variables in nearby counties, WX. Therefore, we need to account for the fact that a change in the value of an independent variable for region *i* affects not only the concentration of dentists in region i, y_i (the value of the estimate from the SDM), but percolates through space to affect nearby neighbor dentist concentrations, y_j, which in turn feed back into dentist concentration in region i, y_i. The summative effect of the two items is termed the "direct impact." Also, we need to account for the fact that a change in the value of an independent variable *r* for region *i* affects the concentration of dentists in region *j*, y_j. This effect is termed the "indirect impact." The "total impact" is the sum of indirect and total impacts. Since these impacts vary by observation, LeSage and Pace compute average impacts, which provide a summary picture of the impact of the marginal change in the independent variable. Statistical tests based on Bayesian Markov Chain Monte Carlo (MCMC) methods, explained further in LeSage and Pace (2009), are used to test for impact statistical significance.

We start our analysis by running a benchmark Ordinary Least Squares regression. This formed the basis for conducting Lagrange Multiplier (LM) tests for the presence of spatial autocorrelation. Five tests were conducted: (a) the simple LM test for error dependence (LMerr), (b) the simple LM test for a missing spatially lagged dependent variable (LMlag), (c) the robust LM test for error dependence (RLMerr), (d) the robust LM test for spatially lagged dependent variable (RLMlag), and (e) a blended test for both lagged dependent variable and error dependence (SARMA). The former two are the Lagrange Multipliers incorporating the spatial dependence restrictions (Anselin, 1988). The middle two are LM tests that are robust with respect to misspecification based on the alternative form of spatial dependence (Anselin et al., 1996). SARMA tests for a model involving both spatial errors and spatial lags. Two choices of row-standardized weights matrix (*W*) were used for testing spatial autocorrelation and for estimating spatial econometric models. One was a contiguity-based spatial weight matrix that used the queen criterion (i.e., horizontal, vertical, and diagonal contiguity) to define neighbors. The other was a distance-based spatial weight matrix based on 10 nearest neighbors. The results were not sensitive to the choice between the two weighting methods. Therefore, only the testing and estimation results for 10 nearest neighbors are reported in the next section.

We conducted the tests and estimations using R statistical software. The OLS estimates were obtained using the lm (linear model) function from the base stats package. Spatial autocorrelation tests and spatial model estimations were conducted using functions from the spdep package (Bivand, 2015; 2008) including the functions lm.LMtests (Lagrange Multiplier diagnostics for spatial dependence in linear models), lagsarlm (SAR and SDM model estimation), errorsarlm (SEM model estimation), and impacts (calculation of direct, indirect, and total impacts for the SDM and statistical significance tests).

Each dependent and independent variable was rescaled (or studentized) by subtracting its mean and dividing by its standard deviation. This transformation accomplished two things. First, it reduced muticollinearity as measured by the condition index to a value below 10. Variance inflation factors were already less than 10 and were not affected by these variable transformations. Therefore, multicol-lin-earity is not a problem. More importantly, rescaling was needed to facilitate the matrix inversions that the spatial regression techniques used. This technique was recommended by LeSage and Pace (2009).

Table 2. Results for alternative models.

	OLS Estimate	SAR Estimate	SEM Estimate	SDM Estimate	SDM Lag estimate
(Intercept)				0.0013	
INC	0.0557	0.0301	0.0420	0.0172	0.1185
PINSURE	**0.1270**	**0.1047**	**0.1263**	**0.1355**	**-0.0208**
PCOLLEGE	**0.2395**	**0.2368**	**0.2527**	**0.2663**	**-0.1897**
PMIN	-0.0316	-0.0325	-0.0250	-0.0234	-0.0440
PSENIOR	**0.0626**	**0.0647**	**0.0722**	**0.0816**	**-0.1092**
AREA	0.0015	-0.0002	0.0017	-0.0159	-0.0247
HIGHWAY	0.0091	0.0105	0.0162	0.0272	-0.0716
NETCOM	**0.2015**	**0.2095**	**0.1923**	**0.1984**	**0.1212**
CITY10	**0.0723**	**0.0750**	**0.0839**	**0.0807**	**-0.1844**
CITY25	0.0254	0.0243	0.0227	0.0282	0.0714
CITY100	0.0099	0.0088	0.0068	-0.0020	0.0305
CITY250	-0.0109	-0.0154	-0.0108	-0.0169	-0.0703
CITY500	0.0019	-0.0060	-0.0072	-0.0157	0.1254
CITY1000	**-0.0493**	**-0.0481**	**-0.0524**	**-0.0581**	0.0464
AMENITY	0.0207	0.0103	0.0139	-0.0305	0.0883
CREATIVE	**0.2269**	**0.2199**	**0.2312**	**0.2323**	-0.0784
EDSPEND	-0.0108	-0.0169	-0.0193	-0.0372	0.0752
TAXES	**-0.0537**	**-0.0547**	**-0.0538**	**-0.0595**	-0.0043
SCHOOL	**0.2862**	**0.2872**	**0.2840**	**0.3019**	0.0909
ρ		**0.1421**		**0.1701**	
λ			**0.2479**		
Log likelihood	-3128.632	-3114.517	-3106.431	-3061.431	

Note: Bold numbers show variable that is associated with the dependent variable at the 99% level. N=3,104 observations.

4. Results

The results of the OLS and spatial regressions are presented in Table 2. Coefficient estimates that are statistically significant at the p=0.01 level are highlighted in bold. These results show that consumer demand characteristics are important. Higher insurance coverage (*PINSURE*) and college attainment (*PCOLLEGE*) are associated with increased dentist density. Higher percentages of seniors (*PSENIOR*) are associated with greater dentist prevalence, a result that suggests increased senior dental care spending per capita offsets any effect of lower utilization level. More net in-commuting also boosts the relative number of dentists. Many working-age individuals can be expected to often choose providers close to their workplaces rather than their residences. Some consumer demand variables were statistically insignificant. The minority percentage of population and per capita income were insignificant at the 0.01 level but had the expected signs. Variables reflecting costs of travel such as the presence of an interstate and county land area were also statistically insignificant.

Supply factors are also important. The creative class (*CREATIVE*) variable is statistically significant with the expected sign, suggesting that such amenities attract dentists. Coefficients for *CITY10* and *CITY1000* suggest attraction to smaller cities but repulsion from very large cities. The dental school variable (*SCHOOL*) is positive and statistically significant, while the taxation variable (*TAXES*) is negative and statistically significant as expected.

Table 2 also presents the results of log likelihood tests for each model. Results indicate that SAR and SEM provide a small model fit improvement while SDM represents a larger improvement. In each instance, Log Likelihood Ratio tests for the SDM alternative indicate statistical significance with p-values substantially less than 0.01. Based on this criterion alone, the SDM would be selected. Table 3 shows the results for Lagrange Multiplier tests for spatial autocorrelation for the OLS model. Results indicate the presence of spatial correlation in the OLS regression consistent with spatial effects in the error term. These results do not exclude a SDM specification. The SDM model has an estimated spatial autocorrelation coefficient, ρ, value of 0.1701 that is highly significant. This result indicates that higher nearby county concentrations of dentists have a statistically significant positive effect on dentists per capita. Table 4 provides estimated direct, indirect, and total impacts and p-values for the SDM model. The results are largely consistent with previously reported results.

Table 3. LaGrange Multiplier test results.

Statistic	*Value*	*p-value*
LMerr	51.28858	0.000
LMlag	31.62661	0.000
RLMerr	20.51378	0.000
RLMlag	0.85181	0.356
SARMA	52.14039	0.000

Some spillover effects are revealed in the indirect impact results. For instance, the presence of urban areas with at least 10,000 residents has a positive effect on the number of dentists within its constituent county, but it is associated with fewer dentists in peripheral counties. This result suggests that counties with small cities may have scale economies or central place advantages that attract dentists who may also serve customers from peripheral areas. A dental school in one county may increase dentists available in neighboring counties as well as the county where it is located. The interpretations of statistically significant indirect impacts for senior population percentage and net incommuting variables are less straightforward. The negative indirect effect for *PSENIOR* may be explained by a greater unwillingness of seniors in peripheral areas to travel longer distances for dental care. The positive indirect effect for *NETCOMM* may partly reflect features of local economies that are correlated with net incommuting and lead to increased dental utilization but are not adequately captured by the model.

5. Policy implications

Evidence presented here indicates that spatial dependencies exist in the dentist distribution and failure to account for them may slightly bias coefficient estimates. Various explanations have been given for the presence of spatial dependencies. The administrative boundaries, such as counties, used for data collection may not reflect actual service areas (Goetz and Debertin, 1996). Underlying spatial processes such as spatial interaction, spatial diffusion, or spatial spillovers may be evident. Health care professions such as dentists might be expected to cluster because of agglomerative forces such as shared customers or inputs. Alternatively, a relatively high number of dentists in one region might induce lower levels in a nearby region because of "border crossing," while favorable consumer demand conditions in one region might similarly attract providers to adjacent regions. Such results underscore the importance of spatial criteria used in Health Professional Shortage Area (HPSA) designations for underserved areas. Dental HPSAs must be "rational service areas" characterized by "homogeneity with respect to socioeconomic or demographic characteristics" and have "limited interactions with contiguous areas" and should not be contiguous with another area that has adequate capacity to provide services to the area (Orlans, Mertz, and Grumbach, 2002).

Table 4. Decomposition results for direct and indirect effects of variables on dentists per 100,000.

	Direct	Pr(>|z|)	Indirect	Pr(>|z|)	Total	Pr(>|z|)
INC	0.0192	0.5316	0.1444	0.0166	**0.1636**	**0.0039**
PINSURE	**0.1355**	**0.0000**	0.0027	0.9915	**0.1382**	**0.0000**
PCOLLEGE	**0.2639**	**0.0000**	-0.1716	0.0237	0.0923	0.2110
PMIN	-0.0242	0.3400	-0.0570	0.0919	**-0.0812**	**0.0022**
PSENIOR	**0.0801**	**0.0000**	**-0.1132**	**0.0007**	**-0.0332**	**0.0022**
AREA	-0.0164	0.3289	-0.0326	0.3531	-0.0490	0.0598
HIGHWAY	0.0261	0.0417	-0.0796	0.0738	-0.0535	0.2442
NETCOM	**0.2009**	**0.0000**	**0.1842**	**0.0004**	**0.3851**	**0.0000**
CITY10	**0.0779**	**0.0000**	**-0.2028**	**0.0013**	-0.1249	0.0550
CITY25	0.0294	0.1118	0.0906	0.1709	0.1201	0.0967
CITY100	-0.0015	0.8810	0.0359	0.6834	0.0344	0.7284
CITY250	-0.0181	0.3757	-0.0870	0.3068	-0.1051	0.2446
CITY500	-0.0137	0.4437	0.1458	0.0476	0.1321	0.0905
CITY1000	**-0.0575**	**0.0006**	0.0434	0.4924	-0.0141	0.7337
AMENITY	-0.0291	0.4248	0.0988	0.0123	**0.0696**	**0.0056**
CREATIVE	**0.2316**	**0.0000**	-0.0462	0.5551	0.1854	0.0434
EDSPEND	-0.0361	0.0188	0.0819	0.0249	0.0458	0.2109
TAXES	**-0.0597**	**0.0004**	-0.0171	0.7072	-0.0768	0.0637
SCHOOL	**0.3043**	**0.0000**	**0.1691**	**0.0000**	**0.4734**	**0.0000**

Note: Bold numbers show variable that is associated with the dependent variable at the 99% level.

Results also show that varied demand and supply factors affect county dentist availability. Consistent with other studies, local demand factors such as health insurance coverage and educational levels play an important role in dentist disparities. In addition, variables not ordinarily included in multivariate models reflecting commuting patterns and local cultural amenities appear to matter. Localities with more net in-commuting have higher effective daily average populations that indicate more actual potential consumers than population estimates alone indicate. The presence of creative professionals may be a magnet for attracting health care workers. Once such variables are controlled for, more urbanized counties do not have the same drawing power. These results suggest that it is the size of the consumer market and presence of amenities associated with highly urbanized areas rather than size of the city itself that matters. Moreover, the "surplus" dentists may not necessarily be inducing demand but rather serving non-resident commuters.

Some of the statistically significant variables are relatively immutable. Urbanization levels and commuting patterns levels are beyond the scope of direct policy remediation. However, others might be altered by policy initiatives. For instance, it may be possible to increase consumer demand through economic development policy and health care initiatives that expand educational attainment and health insurance availability. Policies that attempt to make a community more attractive to creative class professionals may also have the additional benefit of attracting health care professionals such as dentists. Previous studies have found mixed results for the importance of tax and public expenditure variables for health care professions, but results here indicate that higher tax rates may inhibit dentist location. Success in permanently attracting dentists may depend on a much more comprehensive set of community attributes than ordinarily considered. Therefore, dentist recruitment and retention efforts should not be created in isolation but linked with other community, workforce, and economic development plans and made in collaboration with other communities in the region.

One policy initiative that has garnered increasing attention in efforts to boost the availability of dentists is to establish a new dental school. Previous studies conducted at the state level suggest that conventional medical or dental education has little effect on the availability of physicians or dentists (Bound et al., 2004; Bailit and Beazoglou, 2003). Health care professionals locate primarily on the basis of demand for their services rather than where they were educated. Results here suggest that dental schools are associated with larger dentist workforces within host counties and their immediate regions. The presence of dental faculty and residents is clearly one factor that would boost the workforce. Dental schools may also serve as a magnet for practitioners because graduates develop local attachments and professional relationships or desire to be close to centers of knowledge and innovation (Isabel and Paula 2010). Although it is possible some dental school services may displace ones offered by private-practice dentists, the net workforce effect gauged here is positive.

6. Summary and conclusion

This paper presented a model of dentist location based on a utility maximizing framework and spatial econometric methods. Results indicate that demand factors such as income, private insurance coverage, educational levels, and age composition play a role in dentist disparities. Also, dentists tend to cluster near counties with urban areas consisting of at least 10,000 residents, higher net in-commuting, dental schools, and a greater proportion of creative class professionals employed. Spatial econometric models improve model fit over spatially naïve models and provide evidence of spatial dependencies.

Results suggest that some determinants of spatial disparities are relatively immutable while others might be influenced by policy changes. For instance, urbanization levels and commuting patterns are beyond the scope of direct policy remediation. However, consumer access and utilization could be improved by initiatives that improve educational attainment and health insurance coverage. In addition, efforts to permanently attract dentists should be linked with community, workforce, and economic development plans in collaboration with other localities in the region. Finally, results suggest that dental schools may potentially boost regional dentist availability.

The results here must be interpreted with caution for several reasons because of the limitations of the data used. First, we utilized cross-sectional data that represented the stocks of dentists rather than migration flows. The implicit assumption is that the dentists have located in long-run equilibrium. However, the current location of dentists is the culmination of a dynamic adjustment processes that depend on past migration decisions. Thus, ideally one would utilize dentist migration data. Although public data on healthcare worker migration is not yet widely available, it has been created from occupational licensing masterfiles for physicians (Ricketts, 2010), which permits modeling migration decisions in a manner similar to the regional science migration literature. Second, ecological fallacy remains a possibility because of the aggregate geographical data used. Micro-level data on dentists could also be used to make more valid inferences of locational behavior. Third, reliance on observational data makes it more difficult to make causal inferences for specific policies such as the effect of dental schools on dentist availability. In order to have more confidence that the correlation represents actual causation, it would be necessary to establish that the policy variables are exogenous or utilize statistical methodologies that can correct for policy endogeneity. Methods such as fixed effects panel data regression and double difference allow one to infer causation under the weak assumption that unobserved heterogeneity due to selection is time invariant. However, these methods introduce the challenge of collecting complete cross-section, time series data. Instrumental variables estimation offers a potentially more powerful tool by allowing for time-varying heterogeneity but also presents the additional challenge of identifying appropriate instruments that are highly correlated with dental school placement but not with the dental workforce outcomes. This "treatment evaluation" approach is beyond the scope of this study but represents the natural next step in assessing specific policies to boost dental and health care profession workforces.

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