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Place Matters: The Spatial Effects of Human Service Expenditures

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Abstract: Place matters in human services. Temporary Assistance for Needy Families (TANF) devolves spending to services, most often provided by nonprofit organizations. We argue that this devolution allows for people to “vote with their feet” (Ostrom, Tiebout, and Warren 1961: “The organization of government in metropolitan areas: A theoretical inquiry.” *American Political Science Review* 55:831–42) in seeking jurisdictions where there will be more spending on human services. This paper considers the spatial patterns of human service expenditures, arguing that people of lower Socio-Economic Status (SES) are less likely to benefit from higher human service spending. We use a spatial Durbin regression to indicate the effects of SES on expenditures in a home county as well as the spillover effect to surrounding counties. The results show that while human service expenditures increase as African American and Renter populations increase in a home county, they also indicate that neighboring counties free-ride on the efforts of the home jurisdiction. Likewise, as a population ages, there is a very large free-riding effect. We conclude that the decentralized TANF policy regime allows for jurisdictions to specialize in human services.

Keywords: human services, TANF, spatial regression

1 Introduction

Place matters, particularly when one considers human services. A defining feature of many human services is that they are place-based (e. g. Bielefeld, Murdoch, and Waddell 1997; Joassart-Marcelli and Wolch 2003; Allard 2009; Hillier 2007; Peck 2008). One cannot provide a feeding program over the internet, or an afterschool program from a call center overseas. Proximity to individuals served is particularly important in those human services dedicated to people with low mobility or

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elevated fears of difference (Kissaine 2010; Bielefeld, Murdoch, and Waddell 1997). One could also argue that these populations are the most likely to need services in total and costly services in particular.

The devolution of human service production to private organizations, both nonprofit and for-profit, heightens the need to fully understand the impact of geography on access to necessary services for those most in need. In previous generations, state-produced services were mandated to be geographically dispersed, whether it was a health clinic in each city council district or a mental health institution in each region of the state. Those mandates for spatial proximity faded as the New Public Management movement began to envision a quasi-public marketplace where the supply of services would move to the consumers demanding them (V. Ostrom and E. Ostrom 1999). This paper asks a simple, but provocative question: Do human service agencies spend more where populations with low mobility and socioeconomic status (SES) live? Put differently, is there a specialization in where human service resources are expended?

While this question is both practically and theoretically important, this paper also seeks to introduce a relatively under-used tool in policy analysis: spatial regression. Ordinary Least Squares (OLS) regression has been one of the dominant tools in the social sciences, particularly in nonprofit studies. Place is important in our field, yet it can potentially produce fundamental problems for OLS. Clustering in and across space leads to the autocorrelation of error terms, which in turn leads to biased and inefficient OLS estimators (Cliff and Ord 1973; Cordy and Griffith 1993). Conceptually similar to time series analysis, where one attempts to control for serial autocorrelation by lagging variables over time, spatial regression uses a series of tools to account for clustering over space (Getis 2007). By using these spatial regression tools, researchers can account for the autocorrelation across space, resulting in unbiased estimators (Anselin 1988). The spatial Durbin model used in this paper not only accounts for the effects of spatial dependence, but also indicates the effects of a change in an independent variable in a home unit on the dependent variable in a neighboring unit. With this analysis, we are able to address a fundamental issue in post-welfare reform: do jurisdictions free-ride on the human service expenditures of their neighbors? In particular, do counties with higher socioeconomic status (SES) individuals free-ride on the expenditures of their neighbors?

This research has dual purposes. First, it articulates the impact of socioeconomic status, while controlling for community-level measures of health on human service nonprofit expenditures. We find that increases in African-American population, renter population, and crime, all result in increases in human service expenditures for a home county; importantly, we also find that neighboring units expend less as elderly, African-American, and renter populations increase. This indicates the possibility of free-riding by neighbors. Second,

we introduce the spatial Durbin model as an important tool to disentangle the interaction of units across space. Given that human services are inherently place-based, taking account of geographical space is of paramount concern, yet perils exist in not taking into account spatial dependence. We discuss the nature of spatial dependence and how it can create biased and inefficient estimators.

The data used in the analysis are the National Center for Charitable Statistics, Core Files for 2007–2009. Our dependent variable is the log of human service expenditures per capita in US counties within a region broadly in line with the so-called “rustbelt”, which includes New England, the Mid-Atlantic, and Midwest region. Independent variables representing SES values measured through the 2010 U.S. Census are used as controls. Using GeoDa, a spatial data visualization/regression tool, and R, we compare the spatial Durbin model to a traditional OLS regression. The results indicate that: one, the OLS model inflates the effect size and level of significance for the model; two, the spatial model shows that African Americans and mobile renters do not live in counties with less human service expenses, but does indicate that neighboring counties could be free-riding on the expenditures in the home county. We conclude that this pattern speaks to the highly fragmented pattern of human service provision highlighted in the literature on polycentricity (Ostrom, Tiebout, and Warren 1961; Buchanan 1971; Banzhaf and Walsh 2008).

2 The Movement to Service-Based TANF

The Personal Responsibility and Work Opportunity Reconciliation Act of 1996 (PRWORA) represents a fundamental shift in how the most at-risk populations receive state aid. In broad contours, welfare benefits became contingent upon progression towards employment based on the fundamental assumption that states and/or counties are better positioned to devise benefit packages that best serve their community's needs (Allard 2007). Allard (2009, 36) argues that the Temporary Assistance for Needy Families (TANF) program is no longer an entitlement based on level of need, but is largely dependent on the type of community in which one lives.

The provision of TANF took a second turn in the mid-2000s, as the federal government began to withdraw financial support in significant ways. At the program's inception in 1997, more than two-thirds of cash assistance to needy families for the TANF program came from the federal government. By 2004 only 33% remained in the form of cash (Allard 2007, 308). The philosophical backbone of PRWORA was developed in criticism of the Aid to Families with

Dependent Children (AFDC) policy. This critique suggested that the AFDC policy encouraged a cycle of generational dependency and failed to successfully reincorporate program participants into the workforce. One of the key mechanisms for increasing workforce readiness was the use of non-cash assistance to fund vocational training, childcare, adult education, and non-medical health services (Allard 2007, 305). Nonprofit human service organizations were ideally placed to produce these services. A key provision of welfare reform is the empowerment of states – and in several cases of “second-order devolution” counties (Allard 2007) – to determine both eligibility criteria as well as allocation of funds to human service producers.

The movement towards non-benefit assistance, particularly when taken as part of a larger evolution towards contracted privately-produced human services, highlights the need to consider location as a key variable in understanding the types of human services that at-risk populations can access. There is a nascent literature on the interplay of nonprofit location and the neighboring population (Allard 2009; Peck 2008; Bielefeld and Murdoch 2004; Garrow 2014). One of the very first uses of location in the nonprofit studies literature considered the location of three types of nonprofit organizations – social service, health, and education- in relation to populations within specified distances. In considering Dallas County, Texas, Bielefeld, Murdoch, and Waddell (1997) find that the percentage of minority population, racial heterogeneity, and average income are positively related to proximity to a social service nonprofit. They also find a rapid decay in effect size for all variables as the size of the geographic unit under consideration increases. Peck (2008), examining the Phoenix metropolitan region, finds that there is a positive relationship between the number of human service nonprofits and poverty level, Hispanic population, and renter population; at the same time, she finds that there is a positive relationship between nonprofit expenditures and Hispanic as well as renter populations in 2000.

Bielefeld and Murdoch (2004) move locational analysis to understanding not only the interaction of organizations to their surrounding communities in six metropolitan regions, but then look to the interaction of nonprofit and for-profit organizations in the same mission category. Their findings, while divergent across regions and mission, indicate that spatial clustering (dependence) does exist and that there are different spatial processes across these areas. The research points to necessary caution in conducting spatial analysis that extends beyond spatially-meaningful regions. A tremendous amount of research (Joassart-Marcelli and Wolch 2003; Garrow 2014; McDougale 2015) has been conducted in southern California around the distribution of nonprofit organizations. Joassart-Marcelli and Wolch (2003) find that median income, unemployment rate, and low educational attainment are all negatively associated with the number of nonprofits in a

geography, yet when adjusted for proportion in of the population in poverty, there is a very strong positive effect on the number of nonprofits per thousand poor persons. Lastly, Chen, Guo, and Paarlberg (2014) use a spatial count model (ZIP) to find that unemployment rate, renter rate, and poverty rate are all positively associated with the presence of antipoverty nonprofits in Hartford, Connecticut.

Two measures of access have been used in this literature: measures of density (Bielefeld, Murdoch, and Waddell 1997; Bielefeld and Murdoch 2004), and measures of expenditures by human service nonprofits (Peck 2008; Joassart-Marcelli and Wolch 2003). Research on location has typically been geographically constrained to a region (Peck (2008) considers Phoenix) or a comparison of multiple regions (Allard (2009) examines Los Angeles, Chicago, and Washington, DC), resulting in models that are constrained by considerations of external validity. Does the interaction of SES and nonprofit expenditures in Phoenix differ fundamentally from Los Angeles? We would argue that this is the case given significant idiosyncratic regional differences in race, income, and employment patterns.

An open question from this research is: what is the interaction of human service nonprofit expenditures in one geographic unit on its neighboring unit? The literature on polycentricity in metropolitan regions (e. g. Ostrom, Tiebout, and Warren 1961; Buchanan 1971; Spencer and Walsh 2008) holds that expenditures on services should vary across regions for two reasons: one, different types of people have different needs from their services, and two, the heterogeneous preferences of these groups will lead to a sorting of individuals. At the heart of the concept is the idea that individuals who demand more of something will vote with their feet and locate where more of that service is provided (Ostrom and Ostrom 1999). A corollary is that neighboring units will have quite distinct allocations of services as the sorting process occurs. The result would be a region where the allocation within a home jurisdiction is different, and sometimes diametrically so, from its neighbors.

Using a Spatial Durbin model, we are able to disentangle the relationship between home jurisdictions and their neighbors. This additional piece of information allows us to not only understand whether human service nonprofits locate near low SES individuals, which remains an important issue, but also whether neighbors can free-ride on the efforts of home units.

3 Constructing the Baseline Model

Broadly following the models of Bielefeld, Murdoch, and Waddell (1997) and Joassart-Marcelli and Wolch (2003), we hold that four sets of variables are

important indicators of human service expenditures in a geographical area: socio-economic status, health, residential mobility, and public safety. We add a fifth category, institutional structure, to bring the analysis more in line with the Institutional Collective Action (ICA) literature (Feiock 2013). Table 1 provides descriptions of each variable, its source, and its expected sign. Our hypothesis is two-fold. First, we believe that areas of lower SES conditions actually spend more on human services than counties with higher SES conditions. Second, we therefore hypothesize that counties with higher SES conditions will “free-ride” off counties with lower SES conditions.

Table 1: Data and sources.

Category	Variable	Description	Source	Expected Sign
<i>Dependent variable</i>	HSA expenditures	The natural log of avg. HSA expenditures by county 2008–2010	National center for charitable statistics core files (2008–2010)	
<i>Socio-economic status (SES)</i>	Personal earnings	Avg. personal earnings (\$1,000) by county 2007–2009	2010 census	+
	Hispanic Pop. %	% of county population that is Hispanic	2010 census	+
	Black Pop. %	% of county population that is black	2010 census	+
	Pop density	County population in 2010 per 100 residents	2010 census	+
	Over 65 yrs. Old %	% of county population that is at least 65 years	2010 census	+
<i>Health</i>	Obesity Pct.	Avg. adj. obesity as % of county population 2008–2010	CDC wonder	+
	Infant mortality rate	Avg. infant mortality rates (per 1,000 births) by county 2006–2010	CDC wonder	+
<i>Mobility</i>	%. Renters	% of total housing units that are rental units	2010 Census	+
<i>Crime</i>	Violent crimes	Avg. violent crime per 10,000 population by county 2007–2008	DOJ-FBI	+
<i>Institutions</i>	Republican state	Red state for 2008 presidential election.	Elections.nytimes.com	–

The dependent variable comes from the National Center for Charitable Statistics Core Files (2008–2010). It represents the natural log of average human service non-profit expenditures per county between 2008 and 2010. This dependent variable not only provides a static analysis of the role of spending levels, but it also permits future work comparing pre- and post-recession levels. The dependent variable is log-transformed, improving the distribution of a strong positive skew in the dependent variable.

Average age-sex-race adjusted obesity comes from the Center for Disease Controls’ (CDC) research tool, CDC Wonder, as do infant mortality rates. Average violent crime statistics through 2008 come from the Department of Justice-Federal Bureau of Investigations via the Census website. All other variables come directly from the 2010 U.S. Census.

Table 2: Descriptive statistics.

Statistic	N	Mean	St. Dev.	Min	Max
HSA expenditures	1,018	16.04	2.28	8.97	22.53
Personal earnings	1,018	37.61	8.53	17.28	88.44
Hispanic pop. %	1,018	3.72	4.73	0.35	53.53
Black pop. %	1,018	3.41	5.73	0.02	49.22
Over 65 yrs. old %	1,018	16.16	3.41	7.21	31.45
Obesity pct.	1,018	21.22	1.98	12.89	27.32
Infant mortality rate	1,018	6.23	2.56	0.00	19.40
%. Renters	1,018	22.42	7.07	4.79	76.26
Violent crimes	1,018	2.93	12.76	0.00	259.60
Republic party	1,018	0.27	0.45	0.00	1.00
Pop density	1,018	295.60	1,329.95	2.30	32,940

The descriptive statistics (Table 2) indicate a wide variation in the characteristics of counties across the rustbelt geography. For example, the percentage of black population ranges from a minimum of.02% to a maximum of 49.22%. The standard deviation of the violent crime rate, 12.76, when compared to a mean of only 2.93, shows the tremendous heterogeneity in the rustbelt.

The construction of the database included merging the point data with the polygon shapefile. First, all of the human service nonprofits were “geolocated,” meaning that the address provided in the Core Files was mapped based on its longitude (X) and latitude (Y) coordinates. The addresses are mapped by their X and Y coordinates into “points” and overlaid onto a shapefile of U.S. counties. These points are then aggregated within each county by “joining” them to their home polygon. Finally, we export this new file as a separate shapefile from ArcGIS.

Figure 1: Clustering of average human service expenditures (natural log) in Rustbelt states.

Figure 1 shows a standard-deviation map of the dependent variable, the natural log of average human service expenditures in the rustbelt states. As the map indicates, there seems to be two spatial processes at work. First, there seems to be a process where there is higher expenditures amongst human service nonprofits in the eastern part of the region. This can indicate historical processes, where this type of nonprofit has had a longer time to develop, or it could indicate a commitment by these communities to human services in general and more specifically to the delivery of human services by nonprofit organizations. The second spatial process seems to be an urban one, with strong positive values in cities such as Boston, New York, Cleveland, and Detroit. This may simply be due to the fact that there is a higher population density in these counties, meaning that there will be more demand for human service nonprofits. While unclear, the map may also point to a distinction between urban core counties and the surrounding suburban counties. A map such as this can be used for Exploratory Spatial Data Analysis (ESDA), which is the first step in determining whether there is spatial dependence (clustering) in the data. A visual inspection would seem to show clustering.

Next, we estimated the OLS model. The first column in Table 3 provides the results, along with the Moran's I statistic of 0.178 ($p < 0.05$). This test result indicates there is positive spatial autocorrelation present within the residuals of our OLS model. This leads us to two important conclusions. First, spending on

Table 3: OLS vs spatial model specification.

LN HSN avg. expenditures	Model 1: OLS	Model 2: spatial lag	Model 3: spatial error	Model 4: spatial Durbin	Model 4: independent variable lags
Intercept	16.05*** (0.838)	10.74*** (1.03)	15.27*** (0.086)	12.49*** (1.49)	—
Obesity %	−0.086** (0.031)	−0.069** (0.030)	−0.101*** (0.033)	−0.093*** (0.034)	0.049 (0.050)
>65 yrs. Age %	−0.012*** (0.019)	−0.080*** (0.019)	−0.073*** (0.021)	−0.010 (0.023)	−0.143*** (0.035)
Hispanic Pop. %	−0.005 (0.014)	−0.091 (0.013)	0.001 (0.015)	−0.014 (0.015)	−0.026 (0.024)
Black Pop. %	0.039** (0.013)	0.037*** (0.013)	0.05*** (0.013)	0.039*** (0.013)	−0.046** (0.020)
Renters %	0.065*** (0.010)	0.081*** (.009)	0.097*** (0.011)	0.129*** (0.011)	−0.150*** (0.018)
Personal earnings (per \$1,000)	0.079*** (0.008)	0.056*** (0.008)	0.059*** (0.008)	0.043*** (0.009)	0.034** (0.016)
Violent crimes	0.0191*** (0.005)	0.017*** (0.004)	0.010** (0.004)	0.010** (0.005)	0.036*** (0.009)
Infant mortality rate	−0.020 (0.020)	−0.017 (0.020)	−0.025 (0.020)	−0.017 (0.020)	0.001 (0.040)
Republican state	−1.31*** (0.12)	−1.04*** (0.12)	−1.33*** (0.156)	−1.08*** (0.235)	0.348 (0.277)
Pop. density (per 100)	−0.0064*** (0.00005)	−0.012*** (0.00005)	−0.014*** (0.00005)	−0.018*** (0.00005)	0.03** (0.00012)
Adj. R ²	0.52	—	—	—	
AIC	3,840.3	3782.9	3766.9	3699.2	
Moran’s I	0.18***	0.03	−0.03	−0.02	
ρ	—	0.275***	—	0.302***	
λ	—	—	0.389***	—	

Notes: Statistical significance at the 10%, 5%, and 1% levels are indicated by *, **, *** respectively.
Standard errors are in parentheses.
N = 1,018, for all models.

human services at the county level is a positively spatially related phenomenon, meaning that neighboring counties behave in systematically similar ways. Second, the significant Moran’s *I* statistic means that OLS will generate biased estimators and consequently is not the appropriate tool to estimate the data. Therefore, we need to apply spatial regression techniques to generate unbiased parameter estimates.

4 The Spatial Models

Perhaps the most influential textbook on spatial econometrics (Anselin 1988) introduced two basic spatial models to address spatial autocorrelation: a spatial lag and a spatial error model. The spatial lag model accounts for spatial dependence through a lag of the dependent variable across space. Whereas a lagged variable in a time series model accounts for one the same unit one period backward in time, a lagged spatial model accounts for units that are one-unit away spatially. Sparks and Sparks (2010, 467) describe the intuition behind the spatial lag process in the following way:

A spatial lag model most closely represents a diffusive process in the outcome, implying that the value ... in one location is influenced by that in a neighboring location for that particular...outcome....This type of spatial process for studying...outcomes is probably best suited to the study of infectious diseases and possibly social network processes as they spread among people in different spatial locations.

Therefore, a spatial lag model is used in situations where theory, evidence, or intuition suggest that information spreads across space

A SEM, in contrast, is a local model of spatial influence. Rather than examining spatial flows across the entire spatial region in question, the SEM takes into account regional variations by applying the spatial lag to the error term. As a result, there is no “spatial multiplier” that affects the entire matrix and spatial influence dissipates quickly across space. The SER, therefore, is a better means of estimating local and regional idiosyncrasies than the SAR.

Though the SAR and SEM models have been the workhorses of spatial econometrics for many year, the preferred model in applied work is now the Spatial Durbin Model (SDM).¹ The SDM is similarly to the SAR (actually, the SAR is a special case of the SDM) but it also addresses spatial influence in the explanatory factors as well. LeSage and Pace (2009) argue that this model is preferred over the SAR because it drastically reduces the likely effects of omitted variable bias.

$$\text{LN HSA Spending}_i = \rho WY_{i-1} + X\beta + WX_{i-1}\theta + \varepsilon \quad [1]$$

Equation [1] illustrates the form of the Spatial Durbin Model. The first term includes a correlation coefficient, ρ , spatial weights matrix (W), and the average dependent variable for county i 's neighboring counties. The second term is the traditional matrix of explanatory factors followed by the vector of coefficients. The third term in model illustrates that the SDM estimates the impact of the

¹ For a detailed explanation of the SDM model see LeSage and Pace (2009).

spatial lag for each explanatory factor of county i 's neighbors, X_{i-1} , on county i itself.

5 Results

Table 3 provides the results of all four model specifications. We begin with the OLS (Model 1) results to illustrate the apparent risks of ignoring the effects of spatial autocorrelation. In particular, the coefficients show larger effect sizes as compared to those of the spatial models. Overall, the results indicate several pertinent (although biased and inefficient) findings:

- (1) Counties with denser populations, older residents, unhealthier residents, and/or more crime tend to spend less, on average, on human services;
- (2) Counties in Republican-leaning states spend substantially less on human services;
- (3) Counties with higher proportions of African-American residents and renters tend to have higher human service expenditures;
- (4) Higher income counties tend to spend more on human services.

The Adjusted R^2 of .52 would seem to indicate a reasonable model of what drives human service expenditures. The results seem somewhat anomalous, with variables indicating SES causing different signs in the change of human service expenditures: age, obesity, and crime run opposite of renters and African-American population. One of the frustrations of OLS is that it is unable to pull out the interaction of geographic units on one another.

We test for spatial autocorrelation by estimating the Moran's I statistic on the OLS residuals using R. The metric was positive (0.16) and statistically significant. This result is important. It suggests that neighboring counties do influence one another. Counties with higher spending on human services tend to be next to counties that also have relatively higher spending on human services. The Moran's I statistic is a global measure of spatial association. Hence, it can often mask stronger underlying forces of spatial dependence.

In a heterogeneous and large geography, as indicated by the wide range of the descriptive statistics, one could conjecture that there might be different processes of feedback from one unit to the next. Local spatial dependence is explored in Figure 2. This map calculates Getis-Ord G_i^* z-scores based on the residuals from the OLS model. Here we see substantial variation within spatial dependence at the local level. Moreover, Figure 2 illustrates differing approaches to human service spending at the regional level. The Midwestern states appear

Figure 2: Hot spot map for human service expenditures.

to spend less than the northeastern states. The Moran's I coupled with the Getis-Ord G_i^* illustrate a globally and locally spatial process plays out in human service spending at the county level. As noted above, this spatial dependence creates autocorrelation within the error term, thereby violating the classical i.i.d. assumption. Consequently, the standard OLS procedures for estimating the effects of the covariates result in biased and inefficient estimators. In short, we cannot trust this signal. Next, we estimate the three spatial models discussed in the previous section.

The results of the spatial lag, spatial error, and spatial Durbin models are presented in Table 3. The Akaike Information Criterion (AIC), a measure of the relative amount of information loss as compared to the other models (therefore a smaller number is preferred), suggests that the spatial Durbin model is preferred. Between a significant Moran's I test for global spatial autocorrelation and AIC measures that clearly indicate spatial models are a better fit, OLS will lead to inappropriate results. It also indicates that the SDM model is preferred.

The results illustrate substantial differences between the OLS and SDM estimated coefficients. Three results stand out. First, the OLS approach drastically underestimates the role played by a county's population that is over 65 years of age – it underestimates the coefficient size by more than 9%. Second, OLS dramatically underestimates the effect of a county's share of renters on its human service expenditures. The SDM estimate is more than 5% higher, on average, than the OLS estimate. Third, the OLS estimated impact of population density is less than half of that uncovered by the SDM model. These

differences reinforce what our test statistics suggest. Using OLS to address this question, and consequently failing to account for spatial dependence, would lead to inappropriate conclusions.

In addition to estimating the traditional effects of the explanatory variables on the dependent variable, the SDM also estimates the role of the spatial lag of those independent factors on our dependent variable. These results are shown in the final column of Table 3. The results reinforce the importance of correctly specifying the model. All of the models estimated except the SDM found that the share of the population over the age of 65 within a county was a statistically significant predictor of the dependent variable in that same county. However, the SDM shows that, in fact, it is not the effect of the county's older population on itself, but rather the so-called "spillover effects" from one county onto its neighbors. This negative relationship suggests that as own-county elderly populations rise neighbor-county human service per capita spending tends to fall. Similarly, as own-county shares of rental housing increase, neighbor-county HSA spending per capita tends to fall. This effect is actually stronger than the effect of a county's own share of rental housing on its own human service spending. The only positive spatially lagged variable is population density, suggesting that counties with higher levels of density increase – through positive feedbacks – human service expenditures in neighboring counties.

5.1 Spillover Effects

LeSage and Pace (2009) highlight a common error within the spatial econometric literature. If the spatial econometric model to be estimated contains a spatial lag of the dependent variable or the explanatory variables, it is incorrect to interpret its coefficient as a simple partial derivative. In fact, doing so can lead to substantial errors in interpretation of the results. The interpretation of the actual effects of each variable on the dependent variable is more nuanced.

The SDM model allows researchers to estimate the direction and size of so-called spillover effects (Brueckner 2003). Spillover effects occur when changes in a single county have effects on neighboring (or at least nearby) counties. Following the approach outlined in LeSage and Pace (2009, 70), we estimate the direct, indirect, and total effects of each spatially lagged variable in our model. The results are shown in Table 4.

Direct effects occur when changes in county i have an effect on the dependent variable within county i . In this case, the change in the log of human service expenditures per capita in county i is directly affected by changes in the explanatory factors within county i . Indirect (spillover) effects occur when

Table 4: Spatial Durbin direct and indirect effects.

LN HSN avg. expenditures	OLS	Direct effects	Indirect effects	Total effects
Obesity %	-0.086** (0.031)	-0.091***	0.029	-0.063
>65 yrs. Age %	-0.012*** (0.019)	-0.020	-0.200***	-0.219***
Hispanic pop. %	-0.005 (0.014)	-0.016	-0.040	-0.056*
Black pop. %	0.039** (0.013)	0.037***	-0.047*	-0.010
Renters %	0.065*** (0.010)	0.121***	-0.152***	-0.031
Personal earnings (per \$1,000)	0.079*** (0.008)	0.046***	0.064***	0.110***
Violent crimes	0.0191*** (0.005)	0.013***	0.053***	0.066***
Infant mortality rate	-0.020 (0.020)	-0.018	-0.006	-0.023
Republican state	-1.31*** (0.12)	-1.078***	0.030	-1.048***
Pop density (per 100)	-0.0064*** (0.00005)	-0.016***	0.032***	0.016***

Notes: Effects are estimated in R using the “spdep” package (see “direct and indirect impacts”). *P*-values are estimated using MCMC sampling across 2,000 total iterations. Statistical significance at the 10 %, 5 %, and 1 % levels are indicated by *, **, *** respectively.

changes in county i then impact the dependent variable within a neighboring county j . Finally, the sum of the direct effects and the spillover effects is the total effect of a change in a spatially lagged variable on the dependent variable.

When considering the direct effects, three changes are apparent as compared to the OLS coefficients: (1) age is no longer significant; (2) the effect sizes of renters and density almost doubles; and, (3) the effect size of personal earnings is almost halved. The story largely remains similar to that of the OLS model. As African American and renter populations, as well as crime, increase, so does human service expenditures in a home county. Personal earnings are also positively related to human service expenditures, while population density is negatively related. The interpretation of the direct effects could be that urbanized areas are more efficient in their allocation of human service expenditures, yet African-American and mobile populations have higher expenditures. Lastly, as income increases, there are higher levels of resources in a county that can be put into human services.

This is only a part of the story, and the real value of a spatial Durbin model is apparent when considering the indirect effects. Most strikingly, the indirect effect of the population over the age of 65 is significant, negative, and has a large coefficient. What this means is that for every unit increase in the elderly population in a home county, a neighboring county's human service nonprofits will expend 20% less. As African-American populations increase by 1% in a home county, the neighboring counties will spend 4.7% less. Likewise, an increase in home county renters by 1% results in 15% less expenditures in neighboring counties.

6 Discussion

Our intention with the paper was two-fold: first, we believe that the nascent literature on human service nonprofit location is tremendously important as human services are largely place dependent. The movement to privately-produced human services, hastened by welfare-reform and the subsequent movement away from cash to service assistance, means that both scholars and policymakers would be well-served to better understand the spatial interaction of service supply and demand. Over five years, Congress has cut discretionary spending; states have followed suit, with human services bearing a large portion of the cuts (Boris et al. 2010; Pettijohn, Boris, De Vita, and Fyffe 2013). All funders, whether governments or private philanthropy, face increasing need for a limited amount of resources. Location matters for low SES clients, as their mobility is constrained.

Our study is well-positioned to understand the interaction of human service expenditures across geography. We assume that there is a dynamic process of allocating resources, where nonprofit organizations in one jurisdiction not only must secure funding, but they also need to decide how to allocate those resources. Our results indicate that the allocation of neighboring counties decreases as home county allocations increase with renter and African-American populations. Layered on is the large effect of an increasing elderly population on the expenditures in surrounding counties. It is unclear whether this behavior is free-riding or simply due to the clustering of these populations across the rustbelt region. It would be incorrect to say that this is a process in urban centers, where one might expect to find a higher proportion of African-Americans and renters, as compared to suburban surrounding counties. We find that as density increases, expenditures decrease in the home county and increase in neighbors. This very complex pattern requires future exploration, most likely at a smaller geographic expanse in order to isolate other potential explanatory variables.

One explanation for the patterning of services comes from a long-debated literature on polycentric provision of services in metropolitan regions (Ostrom, Tiebout, and Warren 1961). The hypothesis put forward is that individuals will seek out jurisdictions that best match the allocation of services that they most desire, often called “voting with their feet”. Individuals attempt to maximize their preferences on a host of services that go beyond human services: recreation, education, health, and the arts. The core contention is that jurisdictions will specialize in service allocations, which ultimately can create diametrically-opposed patterns in a region. While we cannot definitively point to the veracity of the Ostrom et al. model, human services remains an important area for the application of this model.

Our second goal of the study is to illustrate that “space is special” (Fotheringham, Brunson, and Charlton 2000). Locational analysis has become more prevalent in nonprofit studies as access to GIS software has become easier. The analysis conducted in this paper uses two open-source software packages: GeoDa and R. GeoDa (<http://GeoDaCenter.asu.edu>) is a simple and intuitive software designed to quickly diagnose whether spatial dependence exists in a dataset, and then apply some of the most common spatial regression models (spatial lag and spatial error) in order to mitigate this issue. Created by Luc Anselin and housed at Arizona State University, GeoDa ensures that any analysis that could have spatial implications can be quickly diagnosed. If there is spatial dependence, the R statistical package (<https://r-project.org>) provides a flexible and up-to-date suite of spatial regression models that go beyond those in GeoDa. Due to its open-source architecture, R allows for rapid updates of the newest spatial models. Our goal was to show that spatial regression is not only important for controlling spatial dependence, but also because it can provide information that helps us explore some interesting questions in public policy. In particular, our interest has been to consider the issues of spatial spillover, which the spatial Durbin model handles particularly well.

The use of spatial regression is limited in nonprofit studies, or even the diagnosis of spatial dependence, yet spatiality can be present even when not apparent. Any quantitative empirical study where clustering or contagion could be at play should lead us to test for spatial dependence. Valuable datasets such as the NCCS core files could exhibit spatiality: studies of financial distress (Never 2014; Hager 2001), financial reserves (Calabrese 2013), market entrance (Mook, Maiorano, and Quarter (2015), voluntarism (Rotolo, Wilson, and Dietz 2015), and donative behavior (Casale and Baumann 2015), all could have clustering of like organizations. Clustering and contagion can also be prevalent in studies of resource flows across actors, where space is more conceptual than physical geography (Frazese, Robert, and Hays 2006, Frazese, Robert, and Hays 2008).

We suggest that a prudent practice would be for scholars to acknowledge that spatial dependence could result in biased and inefficient estimators, and that a Moran's *I* test was conducted to rule out its influence for that particular study.

6.1 Limitations

Our study has several limitations. First, we use the NCCS core files in two ways: to construct our dependent variable and also to geolocate nonprofit organizations. It has been shown that nonprofit Form 990 returns are particularly unreliable (Froelich and Knoepfle 1996), in particular in relation to audited financial statements (Froelich, Knoepfle, and Pollak 2000). We seek to mitigate the unreliability by using a three-year average, rather than a single data point for the dependent variable. While a real concern, we believe that aggregating human service expenditures across a very large geography will help to lessen the systematic errors that can be present in this dataset. The issue of geolocation is fundamental to any study of space. In particular, we use organizational mailing addresses on the Form 990s to locate the organizations in a particular county. This can introduce several types of error as outlined by McDougle (2015). First, organizations may not provide services from the mailing-address location. Second, organizations could provide services from several addresses, while we only capture one location. Lastly, P.O. Boxes might be systematically allocated to smaller organizations, resulting in systematic locational bias; Never (2014) finds that there is not a difference in revenue for human service nonprofits with and without a P.O. Box. Our study uses a large geography, making it very difficult to verify the address of every organization in our dataset. With this in mind, we chose the county as the relevant level of aggregation in order to lessen each of these types of bias. Acknowledging that this does not fully address the criticism, aggregation at the county is large enough to say that we capture most service locations for a human service nonprofit within this geography. Given that this study is predicated on understanding the variation in human service spending over a wide region, we must accept the fact that our use of the NCCS for location can produce a bias.

6.2 Future Directions

It is heartening to see that geography is taking root in the nonprofit studies literature. With access to open-source and free GIS software, we believe that space should grow in importance to the issues of allocating limited resources.

Public policy academics and practitioners face the need to make difficult choices about where to invest in public services; criteria such as program effectiveness or efficiency have been central concerns for many years.

Future research into the source of revenues, whether it is from government contracts, private philanthropy, or fee-for-services could provide a necessary lens on the clumping of values across space. This type of analysis could help policymakers identify where public and private resources flow and address inequities in that flow. We believe that issues of geography should join this group as routine elements of any analysis. The results produced here indicate that human service expenditures are unevenly distributed across the rustbelt counties, with significant free-riding on counties with higher African-American, aging, and renter populations. The policy debate can be around whether this is preferable- as Ostrom, Tiebout, and Warren (1961)) suggest- or whether this indicates that certain jurisdictions are abdicating their duty to funding public services for those most in need.

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