
Nonprofit Supply and Citizen Demand: A Spatial Analysis of the Market for Third Sector Services

Christopher R. Prentice
Rachel Carroll
John F. Brennan
Jeffrey L. Brudney

University of North Carolina Wilmington

Abstract

Much prior research explores the relationship between nonprofit location and various community and market characteristics to determine whether citizen demand drives nonprofit supply. As a widely used “policy tool” of government, nonprofits are expected to be responsive to the needs of the communities they serve. However, results are mixed and it remains unclear whether nonprofit markets are ideally distributed. This article builds on previous scholarship by: first, improving the market characteristics under examination; second, introducing multidimensional constructs for modeling community need; third, applying methodologies that account for spatial dependencies; and fourth, replicating the sector-wide analysis in two nonprofit subsectors. Results indicate consistency across subsector and suggest greater nonprofit supply in areas with less even markets and greater population. Contrary to popular conception, findings indicate evidence of less nonprofit supply in areas with greater demand and some potential “crowding-in” where nonprofit supply rises coincident with for-profit supply.

Key Words: Spatial modeling; Nonprofit supply; SOVI; Community need

Points for Practitioners:

- Policymakers should consider increasing the use of nonprofits as policy tools for providing public goods in areas of greater need for services.
- NC 2-1-1 and similar services in other regions provide a rich source of information about community needs that can be used by practitioners to improve policy and managerial decision making.
- This article illustrates the power of geographic information systems as an analytic tool for understanding spatial patterns and generating other useful insights.

Nonprofit organizations provide avenues for artistic exploration and expression, opportunities to congregate and join in religious activity, programs that address the health and basic needs of a broad array of individuals, and advocacy activities that advance social causes and influence public policy. Understanding the geographic distribution and output of these organizations has critical implications for nonprofit clients, neighborhood development, and the social service and public health delivery systems of which they are a part. Perhaps most importantly – as Yan et al. (2014) note – where a nonprofit is located affects the organization’s ability to respond to the needs of various individuals and social groups.

Several studies explore the relationship between nonprofit location and various

community and market characteristics. Findings from these studies are mixed, however (Harrison & Thornton, 2014; Jeong & Cui, 2020; Kim, 2015; Never, 2011; Never & Westberg, 2016; Peck, 2008; Polson, 2017; Van Puyvelde & Brown 2016; Wo, 2018). According to Yan et al. (2014), “this emerging line of research often suffers from methodological limitations and has yet to benefit from the most recent advances in the statistics literature” (p. 243). This case study takes a first step in responding to Yan et al.’s (2014) call to improve methodological rigor in this area of research by: first, improving the market characteristics under examination; second, introducing multidimensional constructs for modeling community need; third, applying methodologies that account for spatial dependencies; and fourth, replicating the sector-wide analysis in two nonprofit subsectors.

In the next section we consider the question of why nonprofits exist, a necessary baseline for analyzing whether they are appropriately addressing the demand in their environment. After the presentation of theory, we review the previous literature that informed our modeling of nonprofit supply, community demand, and market structure. Next, we present the statistical methods used for this analysis including a description of spatially dependent Bayesian linear regression modeling, an underutilized methodology in public affairs research. We then present the results of our analysis and insights that help move this line of inquiry forward. Notably, our results indicate that the relationship between community demand and nonprofit supply is not well-established. These non-findings challenge the widely-espoused notion (Salamon, 2012; Steinberg, 2006) that nonprofits emerge to address unsatisfied demand and fill gaps left unfulfilled by the for-profit and governmental sectors. Nonprofit output is not only a matter of the economics of supply and demand. We conclude the article with limitations of our study and directions for further study.

Why do Nonprofits Exist?

Scholarship on why nonprofits exist generally fall into two categories: economic theories and values-based theories. In the former – and more dominant – stream of literature, nonprofits exist to serve demand that remains unsatisfied by the government and for-profit sectors (Kingma, 1997; Weisbrod, 1975). Weisbrod’s (1975) demand heterogeneity hypothesis suggests nonprofits emerge to satisfy residual demand and owing to their unique institutional form typically produce collective goods. The ensuing paragraphs provide a brief review of goods and the primary theories that explain nonprofit existence and growth.

Goods

A good is anything consumers value, including services and tangible objects (Steinberg, 2006). In the traditional economic view, there are four types of goods – public, private, collective, and club – produced by either public or private actors. The distinction between the four types of goods is the extent to which they are available to citizens or consumers across two dimensions – excludability and rivalry. The first dimension – excludability – pertains to access; a good is excludable if it is possible to prevent someone from consuming it. The second dimension – rivalry – concerns exhaustibility; a good is rival if the amount of

the good is limited.

Placed in a two-by-two matrix, goods can be classified into four groups. Private goods, such as candy bars or automobiles are scarce economic resources with accompanying property rights. For example, a retailer owns an automobile until such time as a consumer pays the retailer for the car. Access to the good is thus restricted to those consumers with the ability to pay for the automobile, and property rights prohibit others from consuming the good. Thus, private goods are excludable and rival. By contrast, public goods – such as national defense – are non-excludable and non-rival. Public goods are available to all individuals, regardless of one's ability to pay for it. Citizens enjoy the protections of national defense equally and the good is not exhaustible.

Collective and club goods share aspects of private and public goods. Collective (or common) goods are not restricted from access, but are limited in quantity. For example, a shelter provides free accommodations to any homeless individual in a metro area, but the number of beds and the organization's capacity are limited. Thus, collective goods are non-excludable and rival. Conversely, club (or toll) goods are excludable and non-rival. These goods require consumers to pay for access, but one person's consumption of the good does not preclude consumption by others. Common examples include uncongested toll roads, private parks, and public transit.

Demand-Side Economic Theories of Nonprofit Existence

Three-failures theory (Steinberg, 2006) postulates that for-profit, government, and nonprofit sectors each fail to provide certain goods desired by citizens and consumers as a consequence of various pressures or due to inadequacies. In the three-failures approach, 1) nonprofits emerge to correct market and government failures, and 2) government and for-profit firms respond to correct nonprofit sector failures (Van Puyvelde and Brown, 2016).

Market Failure

Market failure concerns the inefficiencies resulting from for-profit provision of public goods and services (Steinberg, 2006). Often considered the first fundamental theorem of welfare economics, market failure emerges from three possible sources: underprovision of goods, overexclusion of goods, and contract failure (Steinberg, 2006).

The for-profit sector fails to provide public or common goods because excludability is necessary for profitability. Given the opportunity, consumers have the motive to enjoy a good without paying (free ride), which undermines a firm's ability to yield a profit. Hence, for-profit organizations do not provide goods where access is free (underprovision). Driven by a focus on maximizing shareholder wealth, for-profit firms increase profits by establishing property rights and charging consumers for access. The second source of market failure arises from the inefficiencies created by the overexclusion of goods. For-profits exclude nonpaying customers from consuming a good even when it is nonrival (e.g., club goods) out of fear of losing paying customers. Consumers unwilling or unable to pay for the good are residual demand that other firms (or sectors) may choose to satisfy.

The final source of market failure is captured by contract failure theory. Where information asymmetries exist between consumers and producers and “consumers feel unable to evaluate accurately the quantity or quality of the service a firm produces,” a nonprofit organization is ultimately preferred to a for-profit firm (Hansmann, 1987, p. 29). Such asymmetries exist when goods are highly complex or technical and consumers lack the knowledge to fairly assess the quality. Information asymmetries are also present when purchasers are not the users of a good (e.g., parents paying for child’s daycare). In such circumstances, for-profit firms have both the incentive and the opportunity to take advantage of customers by providing less service to them than was promised and paid for (Hansmann, 1987).

By contrast, nonprofit organizations are seen by consumers as more trustworthy producers. First, consumers see nonprofits as altruistic actors working for the communal benefit, a notion rooted in the sector’s history of providing alms to the poor and referred to as the “halo effect” (Prentice & Brudney, 2016a). Second, legal restrictions on private benefit and private inurement in nonprofit organizations are believed to reduce incentives to cheat. Nonprofits are required by law to cycle profits back into mission-related efforts and are not allowed to pay out dividends to shareholders, a notion referred to as the nondistribution constraint (Hansmann, 1987). Without shareholder profit as a motivating factor, nonprofits are constrained in their ability “to benefit personally from providing low-quality services and thus have less incentive to take advantage of their customers” (Hansmann, 1987, p.29).

Government Failure

Where for-profits fail to provide goods, government emerges to address unsatisfied demand. Guided by principles of equity, transparency, and representativeness, and unconcerned with profit, government produces public goods that are broadly available (non-excludable) and generally inexhaustible (non-rival). According to Weisbrod (1977), government aims to satisfy the median voter and provides goods that most citizens prefer, resulting in residual unsatisfied demand by those individuals that want more goods or services than the median voter. Consequently, for-profit and nonprofit organizations arise to meet this residual demand. For example, neighborhoods desiring greater levels of policing than their municipality provides may establish neighborhood watch programs or hire private security. Nonprofits are the primary mechanism for addressing government failure when profit is unlikely and the goods have a higher degree of publicness. Indeed, “Many nonprofit firms provide services that have the character of public goods” (Hansmann, 1987, p.29).

Nonprofit Failure

The final component in three-failures theory is nonprofit failure. Nonprofits emerge to fill gaps left by the other two sectors, but are limited in their resources and thus fail to meet consumer demand. Salamon (1987) identified four voluntary sector failures and demonstrated that oftentimes for-profit firms and government step in to support or directly provide goods as a consequence of nonprofit failure. According to Salamon (1987), nonprofits fail due to:

1) resource insufficiencies and the presence of free riders, who consume goods without paying (philanthropic insufficiency); 2) an overemphasis on particular subgroups while ignoring others, thereby creating inefficiencies and unnecessary duplication of services (philanthropic particularism); 3) elite control by wealthy benefactors who may misidentify problems and produce ineffective solutions (philanthropic paternalism); and 4) disorganized practices stemming from a lack of professionalization and an overreliance on volunteer labor (philanthropic amateurism).

In sum, the three-failures approach explains nonprofit existence by demonstrating the residual demand for goods left unproduced by market and government sectors. Notably, this approach also illuminates the importance of evaluating all sectors in an ecosystem when exploring questions pertaining to nonprofit sector growth and density.

Entrepreneurship Theory and Values-Based Theories of Nonprofit Existence

In contrast to the demand-side emphasis of the three-failures approach, entrepreneurship theory “attempts to explain the existence of nonprofit organizations from a supply-side perspective” (Van Puyvelde and Brown, 2016). From this perspective, nonprofit organizations are arenas for experimentation and are founded by entrepreneurs seeking to maximize nonmonetary returns (Anheier et al., 2020). Social entrepreneurs are defined as “innovative, opportunity-oriented, resourceful, value-creating change agents” (Dees et al., 2001, p. 4), who weigh their individual priorities for founding a new entity and the institutional benefits and costs of the nonprofit form (Steinberg, 2006). The primary factors social entrepreneurs consider before starting their nonprofit include: the nature of the preference or consumption behavior they seek to modify in others, their own morals and values, potential funding support for the enterprise, their income and perks, and perceived trustworthiness (Steinberg, 2006; Witesman et al., 2019).

Values-based theories of nonprofit existence suggest that nonprofits are formed for purely expressive purposes. Consistent with notions of pluralism, these nonprofits provide a vehicle for individuals to behave and act collectively in furtherance of certain goals (Carman & Nesbit, 2013). This class of nonprofit organizations include organizations that provide associational benefits and promote, protect, and actualize member values and preferences. These nonprofits are formed for various reasons and cut across the nonprofit landscape. Examples of these mutual benefit and advocacy organizations include: religious entities, service clubs, professional associations, labor unions, recreational leagues, and environmental protection firms. Nonprofits are deemed the appropriate organizational form by these groups for matters relating to transparency, trustworthiness, legitimacy, tax benefits, and other mission-specific purposes (Carman and Nesbit, 2013). With this theoretical basis established, we turn in the next section to the literature that informed our model and influenced the operationalization of our variables.

Dependent Variable: Nonprofit Supply

Pennerstorfer and Rutherford (2019) conduct a systematic literature review of studies that capture nonprofit sector presence in a geographic area and identify the various measures employed by scholars. Despite the dual emphasis in this literature on understanding if “we have enough or too many nonprofits in an area,” and whether “nonprofits are located where they are needed,” previous studies rely routinely on a simple count of nonprofit organizations in a geographic area (Kleinbaum & Klein, 2012; Polson, 2017; Van Puyvelde & Brown, 2016; Wo, 2018; Yan et al., 2014). The problem with relying on counts – i.e., the number of nonprofits in an area – is the great variety in the size of the nonprofits counted and the scope of their activities. For example, the county where our university is located is home to 1,180 tax-exempt nonprofits, but only 364 of those organizations earned more than \$25,000 in revenue and held at least \$25,000 in assets in the most recent tax year. Considerably fewer of these nonprofits – 113 out of 1,180 – exceeded \$500,000 in income and assets (a relatively moderate cutoff for capturing organizational scale). Treating observations within these disparate groups as co-equal does not account for the varied output they produce. The same problem presents in studies where the preferred measure for nonprofit presence is density (i.e., count of nonprofits divided by population). By relying on density as the preferred metric for capturing nonprofit presence, these studies (Brennan et al., 2014; Hayes et al., 2015; Paarlberg & Zuhlke, 2019; Prentice & Brudney 2016b) similarly fail to account for variance in the size and scope of the nonprofits under examination.

Pennerstorfer and Rutherford (2019) contend that nonprofit output is a superior measure for some studies. We concur and accordingly measure nonprofit supply by capturing expense information from public charities in North Carolina in this analysis. Expenses are a representative measure of the economic and programmatic product of nonprofit operations and, hence, are most appropriate for our inquiry. We limit our analysis to public charities – i.e., 501(c)(3) organizations, excluding private foundations. Public charities constitute the subgroup of tax-exempt nonprofits that are most likely to respond to service demands in their region, the focus of this analysis. Other nonprofits, including chambers of commerce, country clubs, and advocacy organizations fall into different tax-exempt classifications and are not of interest in this study. Given the potential for certain nonprofit subsectors to respond differently to client demand and market characteristics, we model our dependent variable – nonprofit supply – in three ways: total expenditures by all public charities, total expenditures by Health charities, and total expenditures by Arts charities. We selected these areas of nonprofit activity because they represent potentially important differences in market structures. Given the strong positive skew associated with these measures, we performed a natural log transformation to normalize the distributions.

Independent Variables: Community Demand and Market Structure

Two primary drivers may help to explain nonprofit supply in a given geography. First, and perhaps most common to this literature, are measures of community demand. If nonprofits emerge to fulfill unaddressed demand, as much nonprofit scholarship contends (Salamon,

2012; Steinberg, 2006), then modeling that demand is of utmost importance for understanding nonprofit supply. The second driver consists of other market characteristics, which may also influence nonprofit supply. These characteristics include: 1) for-profit and governmental supply in industries where nonprofits operate, and 2) nonprofit-specific market structures that promote or inhibit nonprofit supply.

Community Need and the Demand for Nonprofit Services

Prior studies model various community characteristics as proxies for community need to represent the “market for nonprofit services.” These studies use one or more of the following measures in their analyses: poverty rate (Hayes et al., 2015; Van Puyvelde & Brown, 2016), race or ethnicity (Peck, 2008; Wo, 2018; Yan et al., 2014), housing (Peck, 2008; Wo, 2018; Yan et al., 2014), violent crime (Wo, 2018), education (Polson, 2017; Van Puyvelde & Brown, 2016), and employment (Yan et al., 2014). Although useful, these measures are unidimensional constructs that capture only part of the multitudinous types of demand for nonprofit services in a region. Scholars in other fields (e.g., public health, disaster management, environmental resilience) use more comprehensive measures for understanding resource deprivation (e.g., Area Deprivation Index) and vulnerability in communities (e.g., Social Vulnerability Index, Baseline Resilience Indicators for Communities). These validated composite measures incorporate many of the metrics noted above (race, poverty, education, employment, etc.) and others (wealth, urbanicity, housing, rent, population growth, etc.), and are intended to provide a more multidimensional measure of community need.

For this study we use one such measure, the Social Vulnerability Index (SOVI), initially developed by Cutter et al. (2003) and refined over time. We followed the most recent SOVI Recipe (2016), and derived principal component analysis (PCA) scores for each zip code in North Carolina by performing dimension reduction on 29 key variables from the Census Bureau’s American Community Survey (2017, 5-year estimates). The statistical procedure entailed the normalization of the variables; and the performance of the PCA using a varimax rotation with the Kaiser criterion. The resulting components were in line with previous analyses with components characterized by loadings on wealth, age, poverty, ethnicity, and geographic variables. Higher scores on the SOVI represent greater social and economic vulnerability in a zip code, and lower scores demonstrate less vulnerability.

Whereas SOVI captures latent community demand, we contend another form of demand – expressed demand – may also be consequential for understanding the extent to which certain areas have greater or lesser nonprofit output. NC 2-1-1 is an information referral service provided by the United Way of North Carolina with support from governments and nonprofits across the state. Individuals seeking assistance for themselves or others may call 211 to obtain referrals to local nonprofits which provide services that meet their needs (e.g., housing, transportation, health, financial assistance, education, legal assistance, etc.). Call centers are open 24/7/365, and the service may be accessed online as well. NC 2-1-1 provides roughly 170,000 referrals on average per year. For this analysis we aggregated three years of referral data (July 2016 – June 2019) by category – i.e., arts and health, and overall – for each North Carolina zip code. To ensure continuity between our

datasets, we coded requests for services to match these nonprofit subsectors. Our study is the first to incorporate a direct measure of expressed citizen demand for nonprofit output in a geography (i.e., referral requests made to NC 2-1-1) and was made possible through a data usage agreement executed with United Way of North Carolina, the nonprofit agency that operates NC 2-1-1.

Market Structure

Market structure is also consequential for understanding nonprofit output. Yan et al. (2014) observe that where a nonprofit is located influences “its access to important financial and human resources [and] determines the intensity of competition and chances of collaboration” (p. 243). For example, a strong social safety net with numerous health and human service programs offered by county government would attenuate demand and theoretically reduce the number of nonprofits, organizations that are commonly seen as “filling the gaps” left by the other sectors (Salamon, 2012; Steinberg, 2006). Similarly, a robust for-profit market that has multiple providers, lower prices for goods, and in some cases requirements to provide charity care (e.g., hospitals) could reduce the demand for nonprofit services. Jeong and Cui (2020), Van Puyvelde and Brown (2016), and others capture these market characteristics by including variables that measure government and for-profit presence.

Consistent with our argument above that simple counts are insufficient, we attempt to capture the relative output of government and for-profit entities. Similar to our construction of the dependent variable and given the potential for certain subsectors to respond differently to client demand and market characteristics, we estimate for-profit output at the zip code level in three ways: total number of for-profit employees, total number of employees in health for-profits, and total number of employees in arts for-profits. Data on for-profit employees derive from the County Business Patterns’ zip code industry detail files for 2016 and are available by North American Industry Classification System codes. For this analysis we captured data for all industries for use in the sector-wide model, health industry data (codes 62---- through 623220) for the health sector only model, and arts industry data (codes 71---- through 712110) for the arts sector only model. Rather than provide actual counts of employees by establishment, the County Business Patterns data bins the information by category (<5 employees, 5-9, 10-19, 20-49, 50-99, 100-249, 250-499, 500-999, and >1000 employees). In order to estimate of the number of employees by zip code i we used the following calculation:

$$e_i = \sum_{j=1}^9 c_{ij} m_j$$

where e_i represents the estimated number of employees by zip code, c_{ij} represents the counts of establishments by zip code and establishment size category, and m_j represents the mid-range value to represent the number of employees within each

establishment by organization size class ($m = \{3, 7, 14.5, 34.5, 74.5, 174.5, 374.5, 749.5, 1499.5\}$). Any values labeled as 'N' were assumed zero indicating zero industries/employees for that particular zip code and employee size class. Figure S1 in the supplemental file provides histogram representations of these variables.¹ We perform a natural logarithm transformation on these variables for model fitting due to heavy skewness in the data.

Counties in North Carolina are the primary governmental provider of health and human services in their region. To account for the potential downward influence these services may bring to the market, we calculated a suitable proxy for expenditures by these entities. For this analysis we use Internal Revenue Service Statistics of Income (SOI) 2017 property tax data by zip code as a proxy. SOI property tax data are associated very strongly and significantly with county government expenditures ($r = .986, p < .001$). Whereas county government expenditures are only available at the county level, SOI property tax data are reported at the zip code level.

The final market characteristic we include accounts for the degree to which resources are (un)evenly distributed across nonprofit organizations in a region. Paarlberg et al. (2018) contend that more oligopolistic markets decrease efficiency and negatively affect the financial health of some nonprofits. They introduce the Blau Index to this field of inquiry to calculate the (un)evenness of the nonprofit market, and we adopt their measure and calculate the index as follows:

$$\begin{aligned} \text{Blau index} &= 1 - \sum (\text{organization share of nonprofit expenditures in zip})^2 \\ &= 1 - \sum \left(\frac{\text{expenditures}_i}{\text{total expenditures}_j} \right)^2 \end{aligned}$$

Where i represents an individual nonprofit and j represents nonprofits aggregated at the zip level. The index ranges from 0 to 1, with higher scores indicating a more even market (i.e., output is more evenly distributed across nonprofits), and lower scores indicating more oligopolistic market where fewer large organizations account for a large portion of the nonprofit output.

Data and Methodology

Table 1 displays summary descriptive statistics for total nonprofit supply and for nonprofit supply in the health and arts subsectors. The values displayed in the table are presented prior to the natural logarithm transformation and suggest, as expected, that total nonprofit supply is the largest, and that the health subsector dominates much of that supply. Also as expected, arts constitute a much smaller segment. These values demonstrate the necessity for a transformation prior to model fit due to skewness. Choropleth maps of the transformed variables are available in supplemental figure S4.

¹ The supplemental file can be found in the following repository: <https://github.com/prenticecr/211.git>

Table 1. Nonprofit Supply by Nonprofit Subsector in USD Across All 770 Zip Codes

| Variable | Mean | SD | Minimum | Maximum |
|---------------------------|-------------------|-------------------|---------|-------------------|
| Total Nonprofit Expenses | 5.4×10^7 | 3.3×10^8 | 0 | 6.4×10^9 |
| Health Subsector Expenses | 2.9×10^7 | 2.7×10^8 | 0 | 6.3×10^9 |
| Arts Subsector Expenses | 5.3×10^5 | 2.7×10^6 | 0 | 5.7×10^7 |

Notes: Values are presented before natural log transformation. Variables are calculated by adding all expenses for all nonprofit organizations, health subsector expenses, and arts subsector expenses in a zip code. Data are sourced from the National Center for Charitable Statistics' 2015 Core files.

Dealing With Missing Information

All variables, aside from the number of for-profit employees, had some level of missing data (see the specific amounts and distributions in supplemental table S1 and figure 2S). 632 of the 770 (82.1%) NC zip codes have no missing information, and of those with missing, most were missing in more than one variable. While the missing data appear spatially random across the state, relationships with the outcomes were detected such that areas with missing information have significantly less nonprofit supply, after imputation. The amount of missing data and the spatial patterns in those missing data are the same across all three models – i.e., for the total nonprofit sector as well as in the health and arts subsectors.

To deal with the missing data, we performed a method of imputation whereby missing values were replaced with the median value of the available first-degree neighboring zip codes – i.e., zip codes that share a common border. We consider this approach an appropriate method because of the strong spatial autocorrelation present in all variables. We assessed this spatial autocorrelation via the Moran's I statistic (Li et al., 2007; Moran, 1950), and all p-values were less than 0.001 indicating a highly significant presence of spatial autocorrelation (see details about this statistic in supplemental materials section 1.1. and the associated Moran's I values in supplemental table S2). Supplemental figures S3-5 display choropleth maps and correlation matrices for all variables, and are organized by nonprofit subsector when appropriate. These maps visually confirm the strong spatial nature of and moderate to high correlation among all variables considered. We also note similar spatial patterns between the total, health, and arts nonprofit subsectors, where health accounts for a larger portion of the total than arts.

Spatially Dependent Linear Regression

A spatially dependent Bayesian linear regression model furnished our means of examining the relationships of nonprofit supply with community need and market structure. This model is superior to more common methodologies in public affairs (e.g., ordinary least squares) because it accounts for spatial autocorrelation evident in most geographic data. For each of the nonprofit subsectors, we considered a baseline model with no spatial random effects, an uncorrelated random effects model, and a correlated random effects model. The baseline model is functionally equivalent to ordinary least squares regression and is included as a basis

for comparison. The uncorrelated random effects and correlated random effects models offer advances upon the baseline by including the spatial random effects to account for and estimate any additional spatial variation in the outcome (expenditure) beyond what can be explained by the independent variables. Full hierarchical specification of these models is expressed as (Lawson, 2013; Lawson & Lee, 2017; Lesaffre & Lawson, 2013):

where y_i is the outcome of interest; X is the design matrix of predictor variables; β is the vector of parameter estimates; w_i , u_i , and v_i create the spatial random effect; and τ is the precision parameter needed for full hierarchical specification (Carroll et al., 2015). For the

$$\log(y_i) \sim \text{Norm}(0, \tau_y^{-1}) \quad (1)$$

$$\log(y_i) = X_i' \beta + w_i \quad (2)$$

$$\beta \sim \text{Norm}(0, \tau_\beta^{-1}) \quad (3)$$

$$w_i = \begin{cases} u_i & \text{uncorrelated} \\ u_i + v_i & \text{correlated} \end{cases} \quad (4)$$

$$u_i \sim N(0, \tau_u^{-1}), v_i \sim N\left(\frac{1}{h_i} \sum_{m=1}^{h_i} v_m, \frac{1}{h_i \tau_v}\right) \quad (5)$$

$$\tau \sim \text{Gamma}(2, 1) \quad (6)$$

spatial random effect, the uncorrelated option assumes random identical and independently distributed variation across the state, while the correlated option assumes spatial correlation in the random effect structure, such that closer spatial areas are assumed to be more alike. This correlated model is known as the conditional autoregressive model (Besag et al., 1991; Besag & Green, 1993). The baseline models evaluate $\log(y_i) = X_i' \beta$.

Model goodness of fit and comparisons were accomplished by examining both deviance information criterion (DIC) and Watanabe-Akaike information criterion (WAIC) (Spiegelhalter et al., 2002; Watanabe, 2010). These measures are functions of the models' deviance estimates such that smaller values indicate a better fitting model, and a difference of four units is considered a significant difference in fit (Spiegelhalter et al., 2002; Watanabe, 2010). See supplement methods section 1.2. for more complete details of these measures.

These analyses were performed with R statistical software (R Core Team, 2015): fillmap (Carroll, 2016), INLA (Blangiardo et al., 2013; Martins et al., 2013; Rue et al., 2009; Simpson et al., 2012), car (Fox & Weisberg, 2019), rgdal (Bivand et al., 2019), spdep (Bivand et al., n.d.; Bivand and Wong, 2018), maptools (Bivand & Lewin-Koh, 2001), viridis (Garnier, 2018), visdat (Tierney, 2017), and corrplot (Wei & Simko, 2017). INLA provided the means of model fitting via the integrated nest Laplace approximation for Bayesian inference (Blangiardo et al., 2013; Martins et al., 2013; Rue et al., 2009; Simpson et al., 2012). INLA is commonly deployed in epidemiology and other scholarly fields that require

accounting for spatial dependencies, but is relatively new to the public administration and affairs literature (Scott, 2016). All other packages aided in plotting and working with spatial data.

Results

Table 2 displays parameter estimates for each of the models – all nonprofit organizations, health subsector, and arts subsector – generated by the best fitting model. Goodness of fit measures in table 3 demonstrate the uncorrelated random effect model achieves the best fit in these data. Estimates were nearly identical within category for model fit, and the direction of the relationships and their statistical significance is fairly consistent across models. Some differences in the magnitude of estimates appear, particularly for the Blau index. Notably, the community demand variables do not have much effect on nonprofit supply. SOVI is not statistically significant in any of the models and NC 2-1-1 requests only achieve statistical significance in the health subsector model and results work in the opposite direction to theory. We find less nonprofit supply in areas with greater NC 2-1-1 health requests – i.e., more expressed community demand.

Other results indicate greater nonprofit supply in zip codes with a less even market for the health and arts subsectors, which could be driven by the presence of large hospitals and museums in the zip code. Our control variable – population – is only well-estimated in the health subsector. Supplemental table S3 includes variance inflation measures from the baseline model fit; none of these is greater than five, which suggests no issue with collinearity.

Table 2. Mean Parameter Estimates and 95% Credible Intervals From the Uncorrelated Random Effect Models

| Parameter | Total Nonprofit Expenses | Health Subsector Expenses | Arts Subsector Expenses |
|-------------------------|--------------------------|---------------------------|-------------------------|
| Community Demand | | | |
| SOVI | -0.01 (-0.15, 0.13) | 0.01 (-0.28, 0.31) | 0.07 (-0.19, 0.34) |
| NC 2-1-1 Requests | 0.11 (-0.17, 0.38) | -0.26 (-0.50, -0.03)* | 0.04 (-0.17, 0.25) |
| Market Supply | | | |
| For-profit Output | 0.33 (0.12, 0.54)* | 0.87 (0.65, 1.09)* | 1.06 (0.85, 1.28)* |
| Government Output | 0.47 (0.22, 0.72)* | -0.03 (-0.55, 0.48) | 0.30 (-0.14, 0.74) |
| Blau Index | -0.84 (-2.30, 0.61) | -11.06 (-14.33, -7.79)* | -11.20 (-14.00, -8.40)* |
| Control Variable | | | |
| Population | 0.25 (-0.14, 0.25) | 0.85 (0.12, 1.57)* | 0.17 (-0.40, 0.74) |

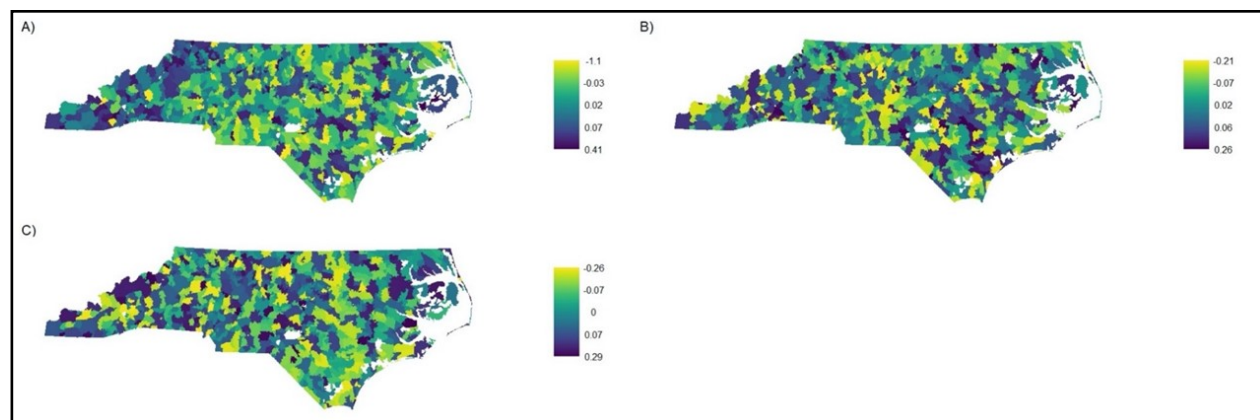
Notes: * indicates a well-estimated parameter – i.e., 95% credible interval does not include 0. N=770.

Table 3. WAIC and DIC Goodness of Fit Measures

| Model | WAIC | DIC |
|------------------------------|---------|---------|
| Total | | |
| Baseline | 4588.99 | 4575.78 |
| Random effect – Uncorrelated | 4571.23 | 4572.49 |
| Random effect – Correlated | 5887.69 | 5865.36 |
| Health | | |
| Baseline | 5766.39 | 5765.20 |
| Random effect – Uncorrelated | 5766.21 | 5764.34 |
| Random effect – Correlated | 6121.91 | 6122.48 |
| Arts | | |
| Baseline | 5610.29 | 5609.77 |
| Random effect – Uncorrelated | 5610.02 | 5607.67 |
| Random effect – Correlated | 5994.96 | 5990.58 |

Note: Smaller measures indicate a better model fit.

The spatial random effects from the best fitting uncorrelated random effects model for each of the nonprofit subsectors are displayed in figure 1 (see supplemental figure S6 for the correlated random effects). These estimates represent residual nonprofit supply after adjusting for the independent variables. Here, higher (darker shading) values suggest more residual nonprofit supply, while lower (lighter shading) values suggest less residual nonprofit supply. This uncorrelated random effect appears mostly random, but some clustering of darker and lighter areas appear (averaging more and less nonprofit supply after adjusting for the independent variables). The west mountain region of the state has more residual total nonprofit supply, parts of the mountain and southeastern regions of the state have more residual health nonprofit supply, and parts of the mountain and piedmont regions of the state have more residual arts nonprofit supply. The correlated spatial random effects (supplemental figure S6) offer very strong spatial structure, and this over-smoothing likely leads to the poor model fit associated with those models.

Figure 1. Uncorrelated Spatial Random Effects From Each of the Models

Discussion

Despite growing recognition that demand-side economic theories of nonprofit formation are incomplete and should be supplemented with other theories (Steinberg, 2006; Ghatak, 2020), they remain central to the literature investigating the size and scope of the nonprofit sector. Demand heterogeneity is the lens through which most empirical research on the relationship between various community characteristics and nonprofit supply is conducted. Paarlberg and Zuhlke (2019) provide a detailed literature review in their analyses that demonstrates the divergent findings of this body of research and the variance in the models and measures used to assess the effects of demand heterogeneity on nonprofit sector size. Lu's (2020) recent meta-analysis finds a significant and positive association between demand heterogeneity and nonprofit sector size, but cautions "the magnitude of the effect is substantially small" and surmises that "its explanatory power in predicting nonprofit sector size and growth might be less robust" (p. 1077).

Prior literature notes significant variability in the measures used in this line of inquiry (Pennerstorfer & Rutherford, 2019; Paarlberg & Zuhlke, 2019; Lu, 2020), and Yan et al. (2014) observe that much of this research suffers from methodological limitations. This article sought to bring clarity to the question of whether demand heterogeneity influences nonprofit sector size by considering multiple types of demand and applying robust statistical techniques to the question. The absence of clear findings for demand on nonprofit supply in our analysis suggests the field should expand beyond demand-side economic theories and incorporate more lenses.

Areas with higher levels of latent and/or expressed community demand could benefit from greater nonprofit activity and yet we do not find any statistical evidence to that effect. Indeed, the only measure of community demand that achieves statistical significance (2-1-1 requests in the health subsector) finds the opposite relationship – i.e., more expressed demand yields less nonprofit supply. We are not able to empirically assess the possibility in our data, but more vulnerable communities with greater demand may lack the resources to support a robust nonprofit sector. It is possible philanthropic insufficiency and philanthropic amateurism are contributing to these findings.

Nonetheless, it appears nonprofit supply might be more influenced by factors other than demand. Findings for the market characteristics appear to be more consequential and suggest a potential complementarity among the sectors that could account for changes in nonprofit supply. For-profit output crowded-in nonprofit supply in all three models. Similarly, government output crowds-in total nonprofit supply. Taken together, these findings suggest some level of interdependence or complementarity between the sectors that warrants further investigation.

Finally, it is possible that the misalignment between supply and demand is influenced by supply-side factors. Entrepreneurship theory and values-based conceptions of nonprofit formation tell us that individuals start nonprofits for myriad reasons beyond demand. Carman and Nesbit's (2013, p. 616) results demonstrate that "personal, emotional, and economic motivations of the founders (i.e., wanting to make a living doing what they love or feeling "called" to do something in a particular area)" are central to understanding why some

individuals start nonprofits. Future theoretical and empirical work is required to understand how these factors influence nonprofit supply.

Conclusion

We introduced new variable constructs, novel data, and improved methods to this line of inquiry in hopes of producing more nuanced results than prior research. And yet, not unlike results from the research we cite, results are mixed. Although some evidence exists for casting nonprofit supply in purely economic terms – e.g., nonprofit health output goes up where expressed demand for health services goes up – the preponderance of evidence produced here and elsewhere in the literature suggests nonprofit supply may emerge for less rational purposes. Despite accounting for latent need (SOVI) and expressed need (NC 2-1-1 requests), those demand variables do not consistently predict nonprofit supply. Rather, other factors in the marketplace seem to be more consequential. It is possible that for-profit and government supply crowds-in nonprofit supply because they are funding nonprofit activity or working collaboratively to produce and deliver services. Since crowding-in could lessen nonprofit service provision in areas not as well served by for-profits and governments, public policy might consider incentivizing nonprofit location where for-profit and government services are less robust.

It is also possible that nonprofit output is influenced by factors not accounted for in other studies and only represented here by the estimated residual spatial variability. We offer multi-dimensional constructs for understanding and capturing community need, but there may be other demand features to consider. Finally, it is possible that there are factors unique to North Carolina that influence findings. Future research might broaden the sample to include more states to account for this limitation and thereby also increase the external validity of any findings.

In conclusion, the research literature on the relationship between the demand for nonprofits and the supply often takes up the questions of whether a sufficient number or too many nonprofits exist in an area, or whether nonprofits are situated where they are needed. Although these questions merit close examination, they typically rely on simple counts of nonprofit organizations as the supply variable, which is a misleading indicator. In the present study, we turn to the broader issue of the relationship between nonprofit location and community and market characteristics. We investigate this research question with stronger measures such as nonprofit expenditures rather than counts, multidimensional indicators of community need such as SOVI, enhanced statistical techniques that account for spatial dependencies, and replication of the sector-wide analysis across the health and arts subsectors. These methodological alternatives can be adopted by future researchers and guide their work.

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About the Authors

Christopher R. Prentice is a Professor of nonprofit management and Founding Director of the Center for Social Impact at the University of North Carolina Wilmington. His research focuses on nonprofit management and cross-sector collaboration.

Rachel Carroll is a Quantitative Researcher with the American Institutes for Research and Adjunct Professor of statistics and data science at the University of North Carolina Wilmington. Her research focuses on spatial and temporal analysis. You can learn more about Rachel by visiting her website: <https://rachelmcarroll.weebly.com/>.

John F. Brennan is an Associate Professor in the Department of Public and International Affairs at the University of North Carolina-Wilmington. He conducts research in American public administration history and issues related to urban economic development. John teaches management, government, and methods courses in his department's undergraduate and graduate curricula.

Jeffrey L. Brudney was the Betty and Dan Cameron Family Distinguished Professor of Innovation in the Nonprofit Sector at the University of North Carolina Wilmington. He published widely in public administration and nonprofit sector studies.