NONPROFIT ORGANIZATIONS IN GENESEE COUNTY, MICHIGAN

By

Andrew T. Guhin

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ABSTRACT

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Background: Nonprofits organizations deliver a variety of crucial goods and services to communities. Given this, it is important to consider if these organizations are located where they are most needed. Previous research on this topic has primarily considered location as a function of the needs and resources in an area. More recently, there has been interest in agglomeration as an additional factor influencing location. This thesis contributes to the literature on this topic by examining the relationship between these factors and nonprofit location. **Methods:** This thesis analyzed National Center for Charitable Statistics (NCCS) and the American Community Survey data from 2013 and 2018 to evaluate nonprofit service providers' location in Genesee County, Michigan as a function of needs, resources, and agglomeration. Service provider location was measured at the census tract level using kernel density estimation. **Results:** First, an Ordinary Least Squares (OLS) model was estimated. A Moran's I test of the residuals indicated significant spatial autocorrelation. A Spatial Durbin model was then estimated, and the percent of renters in a census tract emerged as the only significant predictor of nonprofit location. **Discussion:** Study findings show that most nonprofits included in the dataset are clustered in Flint, an area with high levels of need. However, the towns and cities surrounding Flint showed comparable levels of need, but far fewer nonprofits. This study also reaffirms the need to for researchers to be sensitive to the spatial nature of this type of data.

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INTRODUCTION

Nonprofits are a vital part of American life. While diverse in scope of activity, arguably the most crucial function of nonprofit organizations (NPOs) is in the provision of basic goods and services to communities (Allard, 2009). Compared to nations with large welfare states, in the United States – a more decentralized government with heavy emphasis on voluntarism, localism, and philanthropy – nonprofits are the primary providers for many types of services, with many of them being local, place-based organizations (Lipsky & Smith, 1993). Because of their relevance to community life and people's health and well-being, the geographic equity of nonprofits is an important topic of consideration. The present study is an empirical investigation of nonprofit location in Genesee County, Michigan, and provides unique contributions to the literature on nonprofit organizations, along with useful contextual data. Historically, empirical literature on the location of nonprofit organizations has ignored considerations of spatial statistics (Yan, Guo, & Paarlberg, 2014). This study accounted for previous methodological limitations by estimating a spatial Durbin model. Outside of the scholarly community, the information from this study may be of use to: (a) community members in Genesee County who receive services from these organizations, (b) nonprofit organizations who may have interest in the study's findings, as well as (c) stakeholders in the community, who could utilize the study results to inform decisions related to the service location.

LITERATURE REVIEW

Terms and Definitions

Throughout this thesis, the word "nonprofit" will be used to refer to 501(c)(3) tax exempt organizations. Additionally, the literature reviewed mainly uses three distinct terms - location, sector size, and density – to describe nonprofit activity of some kind in a concentrated area. Many studies will use one description while citing literature that uses another and, for most, the unit of analysis is generally no smaller than a census tract. The term used by the researcher shapes the preceding language used in the paper, the form of the research questions and, sometimes, the variables included in models. This thesis uses "location" throughout to refer to a nonprofit's position in a community, bearing in mind that the level of analysis location is being discussed at is, unless specified, usually at the census tract level or above. If "density" or "sector size" are used, it will be because the cited study used the term, and it was appropriate to describe it in a similar way.

The broad nature of the nonprofit sector makes defining exactly what constitutes a nonprofit organization difficult. In the United States, a primary legal distinction between a nonprofit and a for-profit organization is that the latter can generate and distribute profits to owners/shareholders (Hopkins, 1987). This distinction offers a useful starting point for understanding the sector and some of its behavior. Scholars have further noted that nonprofits are: (a) formal organizations, (b) private, institutionally separate from government, (c) nonprofit distributing, (d) self-governing, (e) voluntary, and (f) serve some public benefit (Salamon, 1999; Hammack, 2002).

Attempts to further define the entirety of nonprofits beyond these broad characteristics become difficult. The sector, like business and government, are highly diverse and carry out many functions. The National Center for Charitable Statistics (NCCS) started the National Taxonomy of Exempt Entities (NTEE) in the 1980's to meaningfully categorize nonprofits and to support the work of researchers and policy analysts (Jones, 2019). Shown by Table 1 below, the NTEE is comprised of ten broad categories and twenty-six major fields. Each major field is further divided into subfields that total close to a thousand categories (Salamon, 2015).

Table 1. *NTEE Categories*

Broad Category	Major Group
I. Arts, Culture, and Humanities	A
II. Education	B
III. Environment and Animals	C, D
IV. Health	E, F, G, H
V. Human Services	I, J, K, L, M, N, O, P
VI. International, Foreign Affairs	Q
VII. Public, Societal Benefit	R, S, T, U, V, W
VIII. Religion Related	X
IX. Mutual/Membership Benefit	Y
X. Unknown, Unclassified	Z

Note. Reprinted from "National Taxonomy of Exempt Entities (NTEE) Codes", by Jones, D., (2019). Retrieved from https://nccs.urban.org/project/national-taxonomy-exempt-entities-ntee-codes#overview

In many ways, the NTEE has been successful in improving nonprofit research. Nearly all researchers studying nonprofits use it to categorize and breakdown data according to their interests and substantive focus. It has also facilitated easier communication between scholars. But it is not without limitations. The main limitation identified in the existing literature is that, while beneficial to nonprofit research, NTEE categories may exclude organizations of interest to researchers (Grønbjerg, 1994; Fyall, Moore, and Gugerty, 2018). For example, if a researcher were interested in studying human service nonprofits, the researcher could simply use the NTEE to exclude all nonprofits other than those with the code "human service." But, it's often not entirely clear what distinguishes a human service nonprofit from other categories. For example, the line separating health and human services is clear in some instances (e.g., a medical research organization vs. a religious antipoverty organization) but is more often blurred (e.g., should a "mental health" organization be classified as a health nonprofit or human service nonprofit?) (Grønbjerg, 2001). Relatedly, some organizations may serve dual purposes and, thus, could fall under multiple categories. Using the previous example, the religious antipoverty nonprofit might be classified as human services, religion-related, or be placed in another category. If a researcher's goal is to capture all organizations in a geographic area that provide human services, they very well may exclude organizations by only using the designated NTEE codes (refer to Fyall et al., 2018 for recent empirical evidence of this). The method section will elaborate more on this and describe how this study plans to address some of these concerns; however, the important takeaway point is that much of the literature reviewed uses NTEE codes and is subject to this limitation.

The Importance of Location

A clear account of the spatial dimensions of inequality and the relevance of location comes from Chapter 3 of Allard's (2009) book "*Out of Reach: Place, Poverty, and the New American Welfare State*." The book focuses on the social safety net within the United States, which includes entities other than nonprofits. However, as previously stated and as the book notes, much of the responsibility for delivering basic goods and services to communities in the United States is shouldered by nonprofits. Researchers who study nonprofits have noted that many of these organizations, especially those providing vital goods and services to communities, are largely local, place-based organizations (Wolpert, 1993; Bielefeld, Murdoch, & Waddell, 1997; Never & Westberg, 2016). Where a nonprofit chooses to locate has important ramifications for communities.

Specifically, Allard (2009) identified three reasons why the location of an organization impacts service outcomes: connectivity, trust, and geographic accessibility. First, part of the argument for shifting more of the burden for service delivery from the state to nonprofit organizations rests on the idea that nonprofits are better connected with local communities (Trudeau, 2008). When someone knows more about a nonprofit, they are more likely to seek them out and interact with them as opposed to unfamiliar ones (Kissane, 2003), and a lack of awareness may result in underutilization of services (McDougle, 2014). Allard asserted that it's expected people will know more about organizations nearer to them than those further away because knowledge of providers is shared between community members. Additionally, many nonprofit's outreach and engagement efforts are typically geographically concentrated, with a focus on increasing local awareness.

Relatedly, trust is important for an organization's success, especially for organizations that offer services that are sensitive, stigmatized, or both. "Trust emerges more naturally when agencies are seen as active and invested members of a community and are connected to local cultural and ethnic identity" (Allard, 2009, p. 50). Many place-based nonprofits work to establish and maintain ties to their neighborhoods and communities for this reason. Literature on social capital and organizations supports this (Snavely & Tracy, 2002; Bryce, 2007; Schneider, 2009). If a nonprofit is located outside of the area where most of its patrons reside, this could damage their ability to form relationships and establish trust.

The last reason Allard identified was that as distance to a service location decreases for an individual, the costs of seeking out services and certain access barriers (e.g., problems with transportation, time spent traveling, willingness to seek out provider) are likely, though not necessarily, to decrease in kind, thereby increasing the chances that the organization and individual interact. More generally, geographic accessibility to amenities (e.g., schools, parks, health facilities, etc.) has been studied by researchers in a variety of fields (Dalton, Jones, Ogilvie, Petticrew, White & Cummins, 2013) and focuses on the spatial equity of amenities. Spatial equity is a concern for this study and others examining nonprofit location because "[…] place matters much more to the success of social programs in a safety net driven by social services than one predicated on cash assistance" (Allard, 2009, p. 14).

Theories Influencing Nonprofit Location

There are a variety of theories on nonprofit organizations, often approaching the subject from different disciplinary perspectives (Anheier, 2006). Many of the theories described below are attempts to explain the existence of nonprofits and do not explicitly theorize why a nonprofit locates where it does. While this review does not exhaust all theoretical perspectives, those included may help explain why a nonprofit would locate in a *particular* community versus another. The approach of this review is like other studies on this topic, where needs, resources, and agglomeration/prior density are all possible explanations to the question: Why does a nonprofit locate where it does?

Heterogeneity and Failure

The primary theories that emphasize the role of community need (which can also be conceptualized in economic terms as "consumer demand," see Grønbjerg & Paarlberg, 2001) in the creation of nonprofit organizations are *market/government failure theory* (Weisbrod, 1977; 1986, 2009) and *contract failure theory* (Hansmann, 1980; 1987).

Market/Government failure theory

A "good" is widely considered to be "public" if it: (a) costs no more to provide to many people than to one, and (b) once provided, there is no way to exclude certain peoples from consuming it. For example, air pollution control is a popular example of a public good. Private firms will not typically provide goods of this type because of the “free-rider” problem (DiMaggio & Anheier, 1990); that is, most people would not choose to pay for a private service offering air pollution control if they could benefit from the service without paying. The question is then, in the presence of market failure, what entity will provide public goods? Weisbrod (1977; 1986; 2009) argued that, in a democracy, when market failures arise the government will provide at least some public goods to the citizenry, and the decision of which goods to provide is part of an elected officials job. For Weisbrod, and for an entire school of political thought, the “median voter” is the primary guide to an official’s decision-making. Theorists have varying descriptions of who included in this subpopulation, but one way is to think of the median voter is by imagining the “statistically average person and the demands she would make on governmental spending policies” (Anheier, 2006, p. 121). According to the theorem, spending on public goods is then reflective of the preferences of the statistically average voter. Under this paradigm, if there is homogeneity in demand for a good or service and the government responds accordingly, then the processes will satisfy voters. However, if there is only a small constituency desiring a good or service (i.e., demand heterogeneity), government officials are not likely to address these concerns or demands. Yet, because the good or service in question is a “public good,” a for-profit firm would likely not provide it either (Anheier, 2006). Weisbrod argued that the existence of nonprofits in a market economy can be explained by this scenario, one where heterogenous demand creates a situation of unmet needs.

As an extension of the median voter theorem, Weisbrod’s argument is vulnerable to critiques of it. As noted by Romer and Rosenthal (1979), these come down to a disagreement about the influence of voters on government expenditure and whether other factors, like bureaucratic inertia and political economy, are more decisive. While there are also critiques of the theory on its own terms, some of which will be discussed in detail further on, what is most relevant for this thesis is the theory's relation to nonprofit location and its marked influence on the empirical literature. For example, a recent meta-analysis from Lu (2017) notes that Weisbrod's theory entails three hypotheses, and the literature on nonprofit location primarily tests one of them, the demand heterogeneity hypothesis. The hypothesis predicts a positive relationship between demand heterogeneity (e.g., diversity of demand) and nonprofit sector size, and Lu notes that this is seen as the fundamental hypothesis for the theory.

To measure demand heterogeneity, researchers have used demographic characteristics such as race, gender, age, sex, religion, etc., as proxy variables. The meta-analysis contained thirty-seven studies that had one or more measures of heterogeneity as a predictor of nonprofit sector size. The analysis framed all the included studies' dependent variables as measuring "sector size," however, many of the individual studies framed their work as investigating location or service access. Overall, the meta-analysis supported Weisbrod's hypothesis of demand heterogeneity, indicating that population heterogeneity had a positive effect in determining nonprofit sector size. Specifically, five of the ten measures were significant and had positive effect sizes, indicating support for the heterogeneity hypothesis: age, education, ethnicity, language, and religion. However, the overall weighted average effect size was 0.034 (p <.001), and the effect sizes ranged from 0.020 to 0.147, which are considered small by most research standards.

Moreover, as Lu (2017) pointed out, measuring heterogeneity is difficult and these results likely reflect that observation. The author recommended using a comprehensive index to measure heterogeneity and focusing on the measures that showed support for the hypothesis. The relationship between a heterogeneity measure and nonprofit sector size is also highly likely to be moderated by the type of work a nonprofit does, which Lu notes as a limitation of the current existing literature and a direction for future research. An analysis of this interaction would be of particular use because some of the difficulty in using demographic characteristics as a measure of heterogeneity is the assumption that ascriptive demographic categories have unified, shared interests, needs, and demands. This assumption may hold true in some cases. For example, Bielefeld and colleagues (1997) found that racial heterogeneity was related to the location of health, social service, and education nonprofits. In their conclusion, Bielefeld and colleagues noted, “We speculate that racial heterogeneity is an adequate measure of diverse preferences because it can be reasonably assumed that each racial group has an equal desire for more of its own type of provider” (Bielefeld et al., 1997, p. 222). The authors seemed to imply that racial segregation of services was desired as the racial diversity in an area increased; this speculation leaves open the question of whether this desire stems from racism, an attempt to account for racial disparities in services, or both. Ben-Ner and Van Hoomissen (1992) found similar results, and stated, “In education, racial diversity enhances [nonprofit] provision, which may be due to resegregation attempts by white parents seeking to avoid the busing of their children to integrated public schools” (p. 409). These authors’ findings may reflect the unified interest of white individuals in an area to racially exclude nonwhite individuals, which could hold across a variety of types of nonprofits. It could also be the case that some characteristics, such as religious heterogeneity, may influence some activity fields (most obviously, religious organizations) more than others (e.g., food, agriculture, and nutrition).

Contract Failure Theory

Hansmann argued that Weisbrod's theory failed to account for the existence of nonprofits that provide goods and services that for-profit organizations also provide (Anheier, 2006). If consumers can: (a) make a reasonably accurate comparison of the quality and price of goods or services offered by different organizations, (b) reach an agreement on the good or service to be provided and its price, and (c) determine if those conditions were met, a for-profit organization should be able to provide goods or services at an efficient level (Hansmann, 1980, p. 843). For a variety of reasons these conditions are often not met (e.g., information asymmetry, the "free-rider" problem, etc.), and the resulting inefficiency is termed a *market failure*.

Hansmann (1980;1987) focused on a specific type of market failure, informational asymmetry – when one party in a transaction has more relevant knowledge than the opposite party – as a way to explain the existence of nonprofits alongside for-profit businesses. In an instance of information asymmetry favoring a business, a consumer may not be able to adequately evaluate a good or service because the business knows more than the consumer does about the product. When the business is aware of this discrepancy, they can use this to take advantage of the consumer. However, Hansmann's argument asserts that, because of information asymmetry, nonprofits have an advantage over for-profit organizations because of their perceived trustworthiness. This trustworthiness comes from the "nondistribution constraint," a key distinguishing mark of nonprofits that prohibits the organization from distributing net earnings to individuals who have ownership in the business. Thus, nonprofits are thought to have little incentive to take advantage of informational asymmetries and consumers will trust the nonprofit over the for-profit organization. In this way, nonprofits may act as a fiduciary, of sorts.

Market/government failure theory has been tested far more than contract failure theory. Perhaps this is because testing the contract theory requires analyzing the market share of nonprofit and for-profit organizations in various sectors along with the population of interests' levels of trust in for-profit business (Corbin, 1999). One study conducted by Salamon and Anheier (1998) tested a host of theoretical perspectives of nonprofits, including contract failure, at a cross-national, country-wide level (i.e., the unit of analysis was a nation's entire nonprofit sector). As a proxy of trust in nonprofits, the researchers used survey data from the World Values Survey, which had a measure of trust in various institutions. Salamon and Anheier used the difference between trust in corporations and average trust in all other institutions to capture trust in nonprofits, and then averaged results across all participants in the survey by country of origin to create one composite score. The authors did not find support for the theory, even after breaking the data down by country and type of nonprofit.

While theoretical concerns have greatly influenced the empirical literature, many studies simply include measures of community need and then test its influence on nonprofit location without much explicit discussion of theory. For example, Peck (2008) found that antipoverty nonprofits in Phoenix, Arizona were located where there were higher levels of need, as measured by the unemployment rate and the number of people under the federal poverty line. However, Yan and colleagues (2014) conducted a study of Hartford antipoverty nonprofits by essentially replicating Peck's study and addressing some of its methodological limitations. As discussed further in the Method section, many studies of nonprofits do not always choose the best model fit for their data and fail to account for spatial variability, both of which could seriously bias observed results, as Yan and colleagues observed (2014). Yet, after accounting for these limitations, the Yan and colleagues (2014) still found that Peck's measures of community need had a significant, positive effect on the number of antipoverty nonprofits in a census tract. So, theory driven or strictly empirical, the literature indicates that community needs are a factor in where nonprofits locate, whether need is operationalized by demographic characteristics or material resources.

Resources

Nonprofits, like for-profits or government entities, require monetary and human resources to carry out their operations (Grønbjerg & Paarlberg, 2001). It is necessary for their survival to maintain revenue streams along with attracting employees, volunteers, or both. This has been termed by some nonprofit researchers as the “resource dependence” perspective. Ben-Ner and Van Hoomissen’s (1991) *stakeholder theory* is useful for considering why a nonprofit might consider an area’s resource base before deciding where to locate. Their theory builds on the failure theories, previously discussed, while also addressing supply side considerations. The authors argued that unmet demand for a good or service cannot alone explain why nonprofits exist. Because nonprofits are inhibited from distributing profits, there must be “stakeholders” sufficiently motivated to form an organization for nonmonetary reasons, but those stakeholders must also be able to provide or secure the resources needed to maintain the organization. The stakeholders are then simultaneously supply and demand side actors (Anheier, 2006). While stakeholder theory does not suggest resources alone motivate location decision making, it leaves room for the idea that the number of nonprofit organizations in an area may be influenced by available stakeholders (i.e., entrepreneurs willing to start an organization, funders, volunteers, etc.).

A key resource provider for nonprofits is the government. At least that’s the main point of Salamon’s (1987; 1995) *interdependence theory*. One of his criticisms of the failure theories was the assumption that governments and nonprofits have a competitive relationship, where nonprofits serve to fill a void left by insufficient responses from markets and governments. Instead, he argued that there is good reason to believe that the nature of the relationship between governments and nonprofits is cooperative and more of a partnership. For unique historical and political reasons, the United States' welfare system is fundamentally different than the European model; rather than directly providing welfare (e.g., something like cash assistance, nationalized health care, etc.,), the government provides and directs funding to third party entities, like nonprofits, as a way to reconcile the desire for public services but general skepticism of government (Salamon, 1987).

Salamon further argued that the two sectors complement one another's strengths and weaknesses. Nonprofits may possess local knowledge that governments do not have and can help to advocate for various causes (Salamon & Anheier, 1998). But, the weaknesses of the sector – termed "voluntary failure" – may showcase its limitations for supplanting government action. "The central failing of the voluntary system as a provider of collective goods has been its inability to generate resources on a scale that is both adequate enough and reliable enough to cope with the human-service problems of an advanced industrial society" (Salamon, 1987, p. 39). Philanthropy is also prone to discriminatory and paternalistic giving, conferring the power to decide between the deserving and the undeserving to those with the most resources. For these reasons, Salamon argued that the governments and nonprofits have an interdependent, complementary relationship.

These two theories, stakeholder theory and interdependence theory, are not necessarily in conflict with one another and have both been used to guide empirical research. Interdependence theory is commonly tested by hypothesizing a positive relationship between some measure of government activity and nonprofit activity. The measure used depends on factors like a study's unit of analysis, geographic scope, and the availability of data. Variables like social welfare spending (Salamon & Anheier, 1998), county library expenditures (Grønbjerg and Paarlberg, 2001), government grants (Luksetich, 2008), and government wages per capita (Kim, 2015) have been previously used by researchers as proxies for government activity. Generally, this theory has empirical support (Lecy & Van Slyke, 2013) but results are not always consistent across studies. A recent meta-analysis (Lu & Xu, 2018) of 30 studies on government size and nonprofit sector size found a significant positive relationship between the two variables; however, the effect was small. The studies included in the meta-analysis differed on important characteristics including year of study, country of origin, measurement of variables, unit of analysis, and type of nonprofit (arts, social services, religious, etc.). However, even after accounting for these moderators, the relationship between government size and nonprofit sector size showed a significant positive but small correlation (r = .063).

As for stakeholder theory and nongovernmental resources on location of nonprofits, the results are mixed. Financial measures of resources are typically used to capture potential revenue streams for nonprofits, which flow from a few sources. Nongovernment sources include things like investments, service delivery fees, and private donations (Fischer, Wilsker, & Young, 2011). While *resources* have been operationalized in a variety of ways depending on the study, generally, researchers have used financial measures and/or characteristics of local populations as proxies. For example, studies have confirmed the relationship between resources and nonprofit location (Peck, 2008; Yan et al., 2014; Never & Westberg, 2016). In an empirical study that tested their stakeholder theory, Ben-Ner and Van Hoomissen (1992) found that communities with more educated, wealthier residents had more nonprofits. Bielefeld et al. (1997) and Corbin (1999) also found that income levels were significantly related to nonprofit location.

Agglomeration Effects

Scholars across a variety of disciplines interested in cities, particularly economists, have long studied agglomeration economies. In the urban economics literature, agglomeration economies are defined as "the benefits that come when [organizations] and people locate near one another together in cities and industrial clusters" (Glaeser, 2010, p. 1). The primary advantage of agglomeration economies is the reduction in transportation costs for goods, people, and ideas (Ellison, Glaeser, & Kerr, 2010). Essentially, agglomeration economies are generally believed to be what drives clustering of people and firms into specific locations (Chatterjee, 2003). Baum and Haveman's (1997) study of hotel locations is a useful illustration of how this process works. The authors hypothesized two different spatial patterns of hotel locations in Manhattan: differentiation and agglomeration. If a newly formed organization was offering a similar product to an already established organization, they may consider differentiating themselves from competitors and maintain a geographic distance. Alternatively, however, the new organization may perceive benefits, like shared infrastructure, information, and reduced consumer search costs, as reasons to locate near established competition. The authors found that hotels located near one another to benefit from agglomeration economies and differentiated themselves from competition through other means, such as size. While researchers have paid considerable attention to agglomeration economies in for-profit industries (for example, see Puga, 2010), a paucity of literature exists exploring agglomeration economies amongst nonprofit organizations.

The limited studies that have tested for it generally find some positive effects, although the results are contingent on factors related to the study. In one of the earliest, if not the earliest, studies exploring this topic, Bielefeld and Murdoch (2004) examined the location of nonprofit education and human service providers and for-profit counterparts in six large metropolitan areas in the United States. Mostly, the authors found little evidence of agglomeration economies, but when there were positive results, findings differed by metropolitan area and type of service. In Boston, nonprofits tended to cluster near for-profit firms, nonprofits in Dallas/Fort Worth tended to cluster near other nonprofits of similar sizes, and in Minneapolis, smaller nonprofits tended to cluster around larger for-profits. Another major study to include a test for the effects of agglomeration on location is da Costa's (2016) study of nonprofits across Brazil. The author specifically focused on religious, advocacy, professional, and cultural organizations. Except for religious organizations, the results showed support for the agglomeration hypothesis. Because these studies have found some initial support for this hypothesis and because there is a significant gap in the literature, the current study may add a much-needed data point to the field by including a test for agglomeration.

CURRENT STUDY

The three explanatory factors presented – needs, resources, and agglomeration – are not necessarily in conflict with one another. Most research acknowledges that no one factor is likely dominant over another, and it is likely that a mix of factors inform where a nonprofit locates. Furthermore, modeling limitations, external validity assumptions, and activity specific results (i.e., the type of nonprofit), likely contribute to the mixed results and lack of clarity in previous literature. To answer the main research question "why does a nonprofit locate where it does?", the following hypotheses were put forward:

1. There is a significant, positive relationship between the number of nonprofits in Genesee County census tracts and levels of need.
2. There is a significant, positive relationship between the number of nonprofits in Genesee County census tracts and levels of resources.
3. There is a significant, positive relationship between the number of nonprofits in Genesee County census tracts and the previous number of nonprofits in a census tract.

METHOD

Study Area

This study exclusively focused on nonprofits in Genesee County, Michigan. Contained within the county is the Flint Metropolitan Area (FMA), one of the most racially segregated areas in the United States (Sadler & Highsmith, 2016). The area's segregation has a deep historical context (Highsmith, 2015) with intentionally discriminatory and racist policies, along with white flight to surrounding townships being key contributors (Sadler & Highsmith, 2016).

Specifically, the "white flight" to the suburbs, combined with the automobile crisis in the late 20th century, contributed to a sharp drop in Flint's population. As the population, and by extension a stable tax base, declined, city government revenues and the available workforce fell in tandem (Reckhow, Downey, & Sapotichne, 2018). The surrounding townships were thus able to provide services for residents, while the city center was left deeply impoverished and sorely underserved (Sadler & Highsmith, 2016). For example, Flint's city government is now operating at less than half of its administrative capacity and represents an extreme case of a nationwide crisis in local government (Reckhow, Downey, & Sapotichne, 2018). Additionally, the Flint water crisis - an egregious instance of environmental racism that poisoned residents of the mostly African American city (Pulido, 2016) - was formally recognized in April 2014. Nearly six years later, the effects of the crisis are still ongoing. Reckhow, Downey, and Sapotichne (2018) noted that the nonprofit sector has historically had a prominent role in Flint, stepping in to provide funding for services when the city could not. Their research indicates it has been particularly key in the aftermath of the water crisis. Nonprofits in the community have collaborated to host meetings, disseminate information, and provide vital services to community members (e.g., bottled water). Further, Flint residents frequently cited nonprofits as important leading organizations in the community. With these facts in mind, Genesee county is a unique setting to investigate what contributes to nonprofit service distribution.

Figure 1. *NTEE Codes of Nonprofits*

NTEE Codes of Nonprofits Included in Analysis			
B60	Adult Education	**P24**	Salvation Army
B90	Educational Services	**P26**	Volunteers of America
B99	Education N.E.C	**P27**	Young Mens or Womens Associations
C20	Pollution Abatement & Control	**P28**	Neighborhood Centers
C32	Water Resources, Wetlands Conservation & Management	**P29**	Thrift Shops
E32	Community Clinics	**P30**	Children & Youth Services
E70	Public Health	**P33**	Child Day Care
F30	Mental Health Treatment	**P40**	Family Services
F32	Community Mental Health Centers	**P43**	Family Violence Shelters
F60	Counseling	**P44**	In-Home Assistance
I20	Crime Prevention	**P46**	Family Counseling
I21	Youth Violence Prevention	**P47**	Pregnancy Centers
I40	Rehabilitation Services for Offenders	**P50**	Personal Social Services
I70	Protection Against Abuse	**P60**	Emergency Assistance
K20	Agricultural Programs	**P62**	Victims Services
K30	Food Programs	**P70**	Residential Care & Adult Day Programs
K31	Food Banks & Pantries	**P71**	Adult Day Care
K34	Congregate Meals	**P73**	Group Homes
K35	Soup Kitchens	**P74**	Hospices
K99	Food, Agriculture & Nutrition N.E.C	**P75**	Supportive Housing for Older Adults
L21	Low-Income & Subsidized Rental Housing	**P76**	Homes for Children & Adolescents
L25	Housing Rehabilitation	**P80**	Centers to Support the Independence of Specific Populations
L40	Temporary Housing	**P83**	Women's Centers
L41	Homeless Shelters	**P84**	Ethnic & Immigrant Centers
L80	Housing Support	**P85**	Homeless Centers
L81	Home Improvement & Repairs	**P86**	Blind & Visually Impaired Centers
L82	Housing Expense Reduction Support	**P87**	Deaf & Hearing Impaired Centers
L99	Housing & Shelter N.E.C.	**P88**	LGBT Centers
P20	Human Service Organizations	**P99**	Human Services N.E.C.
P21	American Red Cross	**S20**	Community & Neighborhood Development
P22	Urban League	**W80**	Public Utilities

Sample Selection

In line with most of the prior literature in this area, nonprofits were selected using the National Taxonomy of Exempt Entities (NTEE), the classification system used by the IRS and the Urban Institute's National Center for Charitable Statistics (NCCS). Health and human services are two of the ten broad categories of nonprofits in the NTEE system; each of these broad categories are further subdivided by specific area activity. For example, the category "Health" is subdivided into four groups, (1) Health Care, (2) Mental Health & Crisis Intervention, (3) Voluntary Health Associations & Medical Disciplines, and (4) Medical Research. Within these groups, there are subdivisions by activity area and type of organization. This thesis was concerned with nonprofits like health and human service providers, specifically those that provide direct services to community members. Within the NTEE categories for health and human services, many were immediately excluded from eligibility. For example, the Medical Research subdivision of Health was excluded, as these organizations do not provide health services.

But there were also organizations that fall outside the health and human service NTEE categories that were included in the analysis. The NTEE is a useful but imperfect way to categorize nonprofits and relying solely on them for inclusion/exclusion presents challenges. The previously discussed definitional problem of human services raised by Grønbjerg (2001) is applicable here. While Grønbjerg wrote about the blurry distinction between health and human services, that blurriness applies elsewhere too. For example, the research on the social determinants of health (SDH) shows that education, ethnicity and cultural orientation, exposure to crime, and spiritual/religious values can impact a person's health (Marmot & Wilkinson, 2005). A reasonable argument could be made that, given the SDH, a religious advocacy nonprofit is an important component of the health and well-being of those involved with the organization. It obviously makes little sense to categorize the religious nonprofit as a health nonprofit for the goals of the NTEE, but for research purposes it is worth considering what exactly a study's aim is and whether solely relying on the NTEE categorizations makes sense. As an illustration of this, Fyall and colleagues (2018) found, for example, that if a researcher were interested in nonprofits providing housing and shelter, only using the designated NTEE category would exclude many nonprofits that clearly provide housing and shelter services based on their mission statements; in their sample of Washington state nonprofits, it excluded 80% of relevant organizations.

Instead of just using NTEE codes, as some studies have done, a more useful strategy is to predefine the relevant population, service type, or SDH of focus, for example, and then either use mission statements to select organizations or include all relevant NTEE codes that match the study's aims. For example, Peck (2008) and Yan and colleagues (2014) defined "antipoverty" nonprofits as those in the following NTEE categories: education, health, mental health, justice, food banks/soup kitchens, shelters, legal services, community development, housing, youth development, residential services, foster care and adoption, and homeless services. Joassart-Marcelli and Wolch (2003) as well as Polson (2017) used similar lists. Likewise, this thesis is concerned with nonprofit organizations that provide direct goods and services to communities. NTEE codes were selected using Reinert's (2011; 2015) list of basic goods: nutritious food, clean water, sanitation, health services, education services, housing, electricity, and security services. Figure 1 shows the list of NTEE codes used.

Dependent Variable

The two most common approaches to measure nonprofit activity are: (a) *nonprofit density*, or (b) *organization expenditures* (Never & Westberg, 2016). The former was approach was adopted for this study and is described in more detail in the following section. Part of this entailed obtaining organization's addresses from the NCCS IRS Business Master File (BMF).

Prior research by McDougle (2015) identified important limitations of the NCCS dataset for nonprofit addresses, including: the use P.O. Box addresses, incorrect addresses, and multiple service locations. The McDougle paper investigated the accuracy of addresses in the NCCS core files dataset, but the issues raised are equally applicable to the BMF dataset because the core files are constructed using the descriptive information from the BMF. In this thesis, if an organization in the dataset listed a P.O. Box as their nonprofit address, the street address was manually identified. Yan and colleagues (2014) were able to successfully do this for roughly half of the organizations in their dataset; the other half were still included in their analysis because P.O. boxes were thought to likely be close to the organization's physical address. McDougle also empirically investigated this question and found that many nonprofits had P.O. boxes in the same area as their operating address, supporting the idea that it is better to keep these addresses in the data set rather than excluding them from the dataset.

Independent Variables

Following prior research, the following variables from the American Community Survey 5 Year Estimate were included in the first models.

Table 2. *Variable List*

Category	Variable	Description	Source & Year
Dependent Variable (DV)	Nonprofit Density per 1,000	The average kernel density per census tract per 1,000 (weighted by total expenditures)	NCCS 2013 & 2018 BMF & Core Files
Independent Variable (IV) - Needs			
	Poverty Level	% of people in census tract below the poverty line	2013 & 2018 ACS 5 Year
	Unemployment Level	% of people in census tract unemployed	2013 & 2018 ACS 5 Year
	% Renter Occupied	% of people in a census tract who rent as a opposed to own their living space	2013 & 2018 ACS 5 Year
IV - Resources			
	Educational Attainment	% of people in a census tract with a bachelor's degree or higher (including professional degrees)	2013 & 2018 ACS 5 Year
	Housing Value	Median housing value in a census tract	2013 & 2018 ACS 5 Year
IV - Diversity			
	Simpson Diversity Index for Race	Index of racial diversity in a census tract	2013 & 2018 ACS 5 Year
IV - Agglomeration			
	Change in Density	Change in nonprofit density from 2013 to 2018	2013 NCCS BMF
Note. IV = Independent variable.			

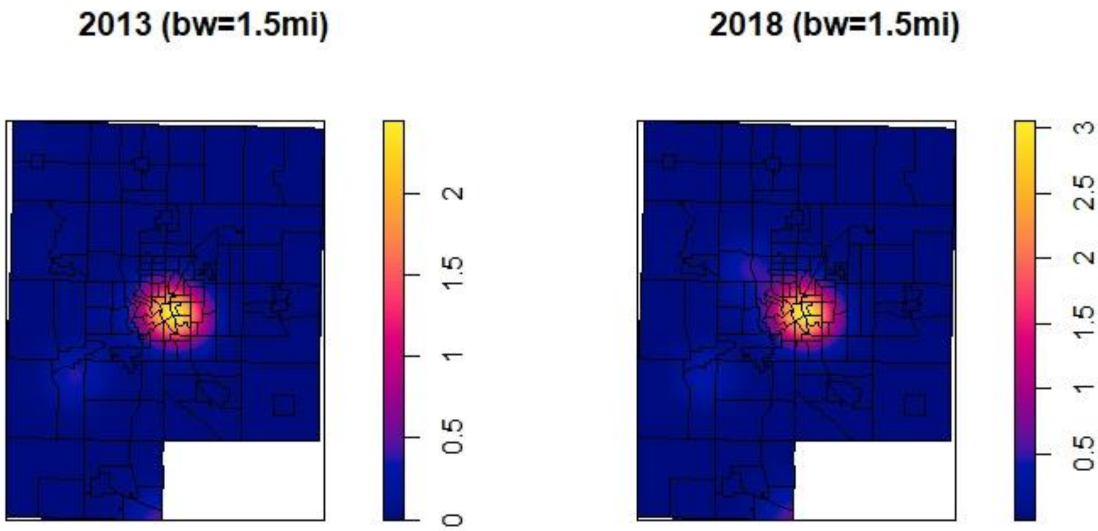
Kernel Density Estimation

To obtain the dependent variable for all analyses, a census tracts' average kernel density per 1,000 people (weighted by each organization's total expenditures), several steps were taken. First, the addresses for all nonprofits active in 2013 (*N* = 60) and 2018 (*N* = 71) in Genesee County, MI with NTEE codes matching those listed in Table 1 were geocoded using Texas A&M's geocoding services. As previously noted, all organizations with PO boxes were included in the analysis. NCCS core files were then used to obtain organization operating expenses

Next, kernel density estimation methods were used to create a continuous density surface of nonprofit organizations. By using kernel density methods instead of quadrat counts – which in this case would entail summing the total number of nonprofits in each census tract – the modifiable area unit problem (MAUP) is avoided (Carlos et al., 2010; Openshaw, 1984). The MAUP is particularly an issue in this study, as an arbitrary boundary like a census tract almost certainly does not reflect interactions between Genesee county residents and nonprofits (i.e., a nonprofit in one census tract can provide services to people in multiple census tracts). A second issue with quadrat counts in this study is that the number of nonprofits in a census tract does not relay any information about the level of expenditures. For example, a tract with five small, low budget nonprofits may spend an amount equivalent to one large nonprofit in another tract. To work around this issue, the kernel function was weighted by total organization operating expenditures.

Of crucial importance for kernel density estimation is the choice of the bandwidth parameter, as this is the search radius that determines the "smoothness" of the point pattern. As the bandwidth increases, the surface becomes smoother and results in less visible variation in point intensity; conversely, as the bandwidth decreases the surface is less smooth and intensity is concentrated near point locations (Anselin et al., 2000). For this study, the bandwidth was set to 1.5 miles for each year to reflect the spatial reach of a nonprofit's services. With the assistance of the TexMix package in R (Tiefelsdorf et al., 2020), after the kernel map was created each tract's average density was extracted, then adjusted for population per 1,000. The final maps are displayed in Figure 2. As the map demonstrates, the nonprofits providing basic goods are heavily concentrated in the Flint Metro Area, with little visible change between 2013 and 2018.

Figure 2. *Kernel Density Map of Genesee County Nonprofit Organizations*



RESULTS

OLS

To begin, an ordinary least squares model was fit for 2018 data with all planned variables included in the model. The results indicated the need for data transformation and model trimming. First, the change variable to measure agglomeration caused severe issues; when this variable was removed, the model substantially improved. Because of its removal, however, hypothesis three could not be directly tested. Although not a test for the agglomeration hypothesis, separate regression models for 2013 and 2018 were subsequently estimated to compare changes over five years.

In each model, the dependent variable, as Table 3 shows, was highly right skewed. To account for this, a Box-Cox transformation was applied. Unemployment rate was log transformed, and one variable - poverty rate - removed to account for multicollinearity. Zero-order correlations are shown in Table's 4 & 5, while OLS results are shown in Table 6. Also included in Table 6 are the Moran's I values for each covariate and for the overall model; to obtain these estimates, a first-order queen contiguity matrix was constructed. The queen matrix defines as a neighbor any spatial unit that shares an edge or vertex.

Table 6 indicates a few important things. With respect to the overall model, each year's model was significant and able to explain over half of the variance in the dependent variable (average kernel density per census tract per 1,000 (weighted by total expenditures), with 2018 performing slightly better (2013 model R^2 = .52, F (5, 123) = 26.25, $p < .001$; 2018 model R^2 = .59, F (5, 123) = 35.21, $p < .001$). The Moran's I value for the residuals – which are plotted in Figure 3 - is significant with each year, indicating residual dependence and that OLS is not an appropriate model choice. With respect to individual covariates, a few things are of interest.

First, there is no change in the direction of the relationships over time although beta estimates do change between 2013 and 2018. The coefficient values for the two variables that lost significance in the 2018 model – Simpson Diversity Index Score and % Rent – each substantially decreased; although, Table 3 indicates little fluctuation in these variables. Median housing value, while significant in each model, had an almost negligible impact. The estimate for educational attainment substantially increased in 2018. Each covariate's Moran's I estimate is positive, significant, and high for both years; this indicates that that these attributes are clustered over space.

Table 3. *Descriptive Statistics*

	2013 (N=129)	2018 (N=129)	Total (N=258)
NPO Density per 1,000			
Mean (SD)	0.151 (0.289)	0.204 (0.376)	0.178 (0.336)
Median (Q1, Q3)	0.010 (0.001, 0.134)	0.016 (0.002, 0.214)	0.014 (0.001, 0.168)
Min - Max	0.000 - 1.340	0.000 - 1.908	0.000 - 1.908
% Rent			
Mean (SD)	0.303 (0.196)	0.307 (0.196)	0.305 (0.195)
Median (Q1, Q3)	0.305 (0.113, 0.435)	0.329 (0.114, 0.426)	0.326 (0.113, 0.434)
Min - Max	0.023 - 0.768	0.012 - 0.873	0.012 - 0.873
Median Housing Value			
Mean (SD)	85,639.535 (44,248.602)	91,424.016 (58,439.876)	88,531.775 (51,812.382)
Median (Q1, Q3)	87,700.000 (45,000.000, 116,300.000)	90,800.000 (33,200.000, 134,100.000)	88,700.000 (41,875.000, 121,800.000)
Min - Max	12,700.000 – 213,400.000	9,999.000 – 262,300.000	9,999.000 – 262,300.000
Simpson Diversity Index Score			
Mean (SD)	0.232 (0.166)	0.234 (0.173)	0.233 (0.169)
Median (Q1, Q3)	0.194 (0.089, 0.356)	0.174 (0.090, 0.395)	0.186 (0.090, 0.367)
Min - Max	0.000 - 0.582	0.004 - 0.650	0.000 - 0.650
Unemployment Rate			
Mean (SD)	0.193 (0.104)	0.125 (0.103)	0.159 (0.109)
Median (Q1, Q3)	0.165 (0.112, 0.261)	0.092 (0.050, 0.183)	0.132 (0.077, 0.213)
Min - Max	0.022 - 0.590	0.008 - 0.509	0.008 - 0.590
% Bachelor's degree or Higher			
Mean (SD)	0.164 (0.103)	0.177 (0.113)	0.170 (0.108)
Median (Q1, Q3)	0.144 (0.097, 0.214)	0.146 (0.094, 0.232)	0.144 (0.094, 0.224)
Min - Max	0.012 - 0.502	0.006 - 0.497	0.006 - 0.502

Table 4. *2013 Zero-Order Correlations*

	% Rent	Median Housing Value	Simpson Diversity Index	Unemployment Rate	% Bachelor's Degree or Higher
% Rent					
Median Housing Value	-.55**				
Simpson Diversity Index	.55**	-.45**			
Unemployment Rate	.47**	-.72**	.32**		
% Bachelor's Degree or Higher	-.34**	.75**	-.19*	-.64**	
NPO Density per 1000	.57**	-.62**	.52**	.52**	-.36**
Note: *$p<0.05$; **$p<0.01$					

Table 5. *2018 Zero-Order Correlations*

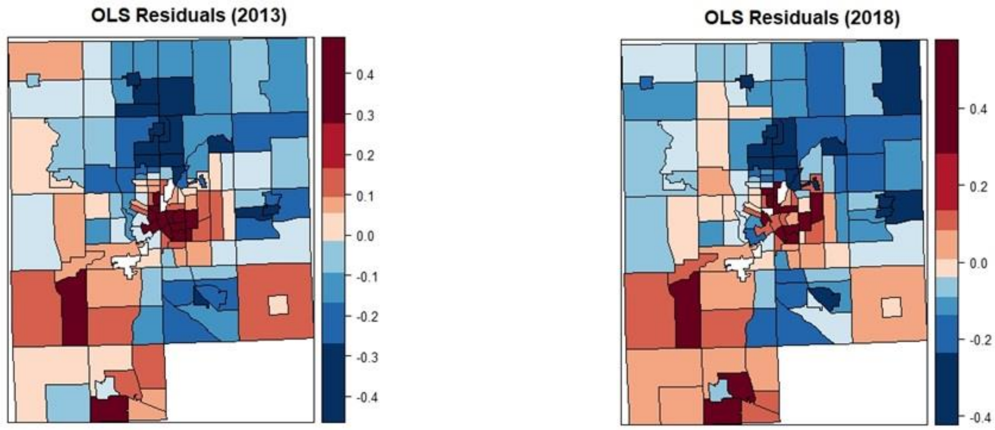
	% Rent	Median Housing Value	Simpson Diversity Index	Unemployment Rate	% Bachelor's Degree or Higher
% Rent					
Median Housing Value	-.59**				
Simpson Diversity Index	.57**	-.47**			
Unemployment Rate	.55**	-.69**	.28**		
% Bachelor's Degree or Higher	-.35**	.79**	-.14	-.56**	
NPO Density per 1000	.54**	-.71**	.48**	.58**	-.41**
Note: *$p<0.05$; **$p<0.01$					

Table 6. *OLS Output with Moran's I values*

	Dependent variable:			
	Density per 1000		Moran's I	
	2013	2018	2013	2018
% Rent	0.333**	0.074	0.454***	0.461***
	(0.127)	(0.130)		
Med. Housing Value	<-0.000***	<-0.000***	0.759***	0.813***
	(<0.000)	(<0.000)		
Simpson Diversity Index	0.332**	0.147	0.589***	0.493***
	(0.142)	(0.141)		
Log Unemployment Rate	0.605*	0.641**	0.547***	0.574***
	(0.342)	(0.306)		
Educational Attainment	0.547*	0.939***	0.603***	0.638***
	(0.294)	(0.284)		
Constant	0.261**	0.518***		
	(0.119)	(0.088)		
Residuals			0.691***	0.609***
Observations	129	129		
R^2	0.516	0.589		
Adjusted R^2	0.497	0.572		
Residual Std. Error (df = 123)	0.213	0.202		
F Statistic (df = 5; 123)	26.250***	35.205***		

Note: *p<0.1; **p<0.05; ***p<0.01

Figure 3. *OLS Residual Plots*



Spatial Models

Because of the significant Moran's I values shown in Table 6 (2013: 0.691, p<.001; 2018: 0.609, p<.001) subsequent models attempted to account for the spatial dependency in the data. A series of spatial regression models were estimated, all using the same queen contiguity matrix previously described. Given the nature of the data, the spatial Durbin model (SDM), both conceptually and empirically, was the best fit. The SDM takes the following form:

$$y = \rho Wy + X\beta + WX\theta + \varepsilon$$

The first term, ρWy, accounts for the influence of a neighboring census tract's dependent variable value; the second term, $X\beta$, is the standard matrix of explanatory variables (i.e., a census tract's own explanatory variables); the third term, $WX\theta$, accounts for the influence of a neighboring census tract's independent variable values. Conceptually, the SDM makes sense for this data because previous literature indicates that the presence of nonprofits in one region may influence the presence of nonprofits in neighboring regions (the lagged y component); additionally,

Table 7. *Lagrange Multiplier Diagnostic*

	df	LM	p
LM Error			
2013	1	173.21	<.001
2018	1	134.65	<.001
LM Lag			
2013	1	186.26	<.001
2018	1	155.49	<.001
LM Error Robust			
2013	1	11.33	<.001
2018	1	6.25	.01
LM Lag Robust			
2013	1	24.38	<.001
2018	1	27.09	<.001

characteristics of a region may influence the number of nonprofits in neighboring regions (the lagged x component); for example, high levels of unemployment rate in one tract leading to more nonprofits in a neighboring tract.

Empirically, the SDM was shown to be the best fit for the data as well. Lagrange multiplier tests, shown in Table 7, on both OLS models indicated model misspecification in the error term as well as the presence of a missing spatially lagged dependent variable. With all four tests significant, this is grounds for defending the choice of the SDM (Anselin, 2013; Golgher & Voss, 2016).

The results from the SDM are shown in Table 8, while Table 9 displays the indirect, direct, and total effects.

Table 8. *Spatial Durbin Model*

	Dependent variable	
	Density per 1,000	
	2013	2018
% Rent	0.077*	-0.002
	(0.040)	(0.052)
Med. Housing Value	-0.00000	-0.00000
	(0.00000)	(0.00000)
Simpson Diversity Index	0.057	0.019
	(0.054)	(0.057)
Log Unemployment Rate	0.190*	-0.045
	(0.102)	(0.122)
Educational Attainment	0.015	-0.071
	(0.098)	(0.122)
Lag of % Rent	0.251***	0.222*
	(0.093)	(0.120)
Lag of Med. Housing Value	0.00000	-0.00000
	(0.00000)	(0.00000)
Lag of Simpson Diversity Index	-0.114	-0.151
	(0.092)	(0.108)
Lag of Log Unemployment Rate	-0.369	0.124
	(0.236)	(0.219)
Lag of Educational Attainment	-0.341*	0.380*
	(0.206)	(0.229)
ρ	0.981***	0.937***
Constant	-0.049	-0.008
	(0.070)	(0.065)
Observations	129	129
Log Likelihood	161.011	138.514
$sigma^2$	0.003	0.005
Akaike Inf. Crit.	-296.023	-251.027
Wald Test (df = 1)	7,180.304***	1,195.225***
LR Test (df = 1)	244.133***	183.737***

Table 9. *SDM Effects*

	Direct Effects	Indirect Effects	Total Effects
% Rent			
2013	.337***	7.206***	7.544***
2018	0.123	2.865*	2.988*
Med Housing Value			
2013	<0.001	<0.001	<0.001
2018	<-0.001	<-0.001	<-0.001
Simpson Diversity Index			
2013	.009	-1.334	-1.325
2018	-0.057	-1.739	-1.796
Log Unemployment Rate			
2013	0.043	-4.153	-4.110
2018	0.001	1.065	1.067
Educational Attainment Rate			
2013	-0.245	-7.246	-7.492
2018	0.108	4.092	4.199
Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$			

In addition to the Lagrange Multiplier results from Table 7, the SDM's AIC value was lower than those from a Spatial Error Model and a Spatial Lag Model (not included here), further suggesting that the SDM is preferred. A few results from Table 8 compared to those from Table 6 standout. First, median housing value, while maintaining its negative direction, loses its significance. Educational attainment and unemployment rate lose significance, change direction, and coefficient values are substantially reduced, suggesting the OLS model overestimated their importance. The only variable significant between both years is the lag variable for the percentage of people renting in a tract. The results from Table 9, which are necessary to properly interpret the SDM results according to LeSage and Pace (2009), support the finding on percent renting from Table 6; that is, the model suggests that in each year the percent renting in a census tract positively influenced neighboring tract's density, and in 2013 the percent renting rate in a census tract also influenced the density in the same tract, though this is not as strong of an effect compared to the lag.

DISCUSSION

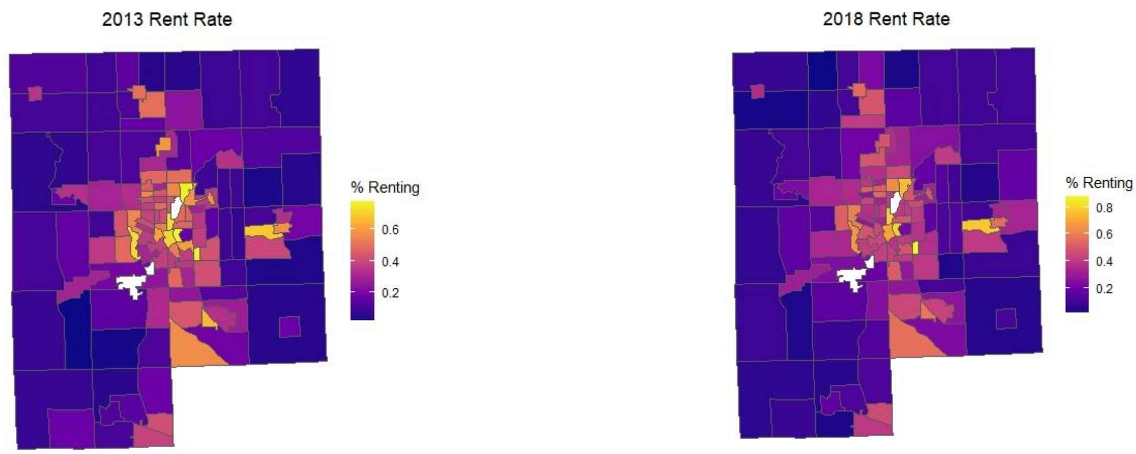
This study set out to test the influence of three factors in determining nonprofit location in Genesee County, Michigan: needs, resources, and agglomeration. Each factor was hypothesized to have a positive relationship to the density of nonprofits in an area. The results of the study demonstrated the importance of spatial modeling to assess this research question and provided useful information about each of these factors relationship to nonprofit density.

A number of researchers among transdisciplinary fields conducting research related to social problems influenced by explicit spatial elements, such as, ecology (Beale et al., 2010), demography (Voss et al., 2006), and econometrics (Pace & LeSage, 2004), have emphasized the importance of accounting for spatial autocorrelation in regression models. Left unaccounted for, spatial autocorrelation can increase type 1 error rates (Beale et al., 2010) and inflate parameter estimates (Mauricio Bini et al., 2009; Lennon, 2000). In comparing the results between OLS and spatial models, it is readily apparent that far fewer variables are statistically significant and coefficient estimates are substantially smaller in the spatial models, with some also shifting in the opposite direction. These results indicate the potential pitfalls of nonspatial models for this type of data. That is, had this study only used OLS models, both of these issues would have gone unnoticed and inaccurate conclusions would have been drawn. Fortunately, researchers in nonprofit studies do utilize spatial regression methods and have for some time (see Bielefeld and Murdoch, 2004 for an earlier example; for more recent ones, Yan et al., 2014, or Never and Westberg, 2016), although it is hard to gauge their current prevalence. At minimum, testing model residuals for autocorrelation should become a best practice for this line of research, given the spatial nature of the data.

As for the hypotheses, this study was able to statistically test two of the three hypotheses initially proposed: that a tracts' resources and needs would both have a positive relationship to nonprofit density. The results from the final spatial model found limited support for the needs hypothesis, and no support for the resources hypothesis. For each year, the only significant variable in Table 8 was the percent renting in a census tract. In 2013, all effects for percent renting were statistically significant, while in 2018 only the indirect and total effects were statistically significant. This finding is consistent with prior research (Peck, 2008; Yan et al., 2014; Never and Westberg, 2016) and provides some evidence that the nonprofits of focus – those providing basic goods and services – are located in areas where they needed.

Interestingly, the "spillover" (i.e., the indirect) effects were much larger than the direct effects, meaning that a tract's rental rate has a stronger impact on neighboring tract's nonprofit density than on its own. An examination of Table 9 reveals the indirect effects are larger for all variables. One way to make sense of this finding, along with coefficient values and directions, is by examining choropleth maps for the variables. The Appendix includes choropleth maps for all the variables, but Figure 4 only shows the percent renting in a tract. As can be seen, in the tract surrounding Flint - Mount Morris and Mount Morris Township, West Burton, Beecher, and parts of Genesee Township – the percentage of residents who rent is fairly high, especially compared to the outskirts of the county. But when examining Figure 1 – the Kernel maps – it's seen that the density in these areas is not as high as the core metro area of Flint. This would explain the "spillover" seen in the significant and large indirect coefficient.

Figure 4. *Percent Renting in Genesee County*



The nonsignificant results are also themselves interesting and useful to investigate. First, following the theoretical literature on diversity and nonprofit organizations, a Simpson Diversity Index for race was calculated and included in models as a proxy for need. Its non-significance and small coefficient size in the spatial models imply extremely limited influence, if any. One reasonable explanation, hinted at earlier in the literature review, is that heterogeneity is usually not by itself a reliable indicator of needs and preferences, and in the instance it is, then this is true for a limited class of things. People who are members of some group (e.g., a race, an ethnicity, a religion, etc.), are themselves diverse individuals with membership in many other groups. Sometimes, an individual's particular need or preference may be directly related to their membership in a certain group; if enough people in that same group share the same need or preference, and a nonprofit could meet this, then it makes sense to anticipate a relationship between the number of nonprofits in an area and the diversity along some group membership. For example, it would make intuitive sense to expect a relationship between religious diversity and the number of religious nonprofits in an area. In this study, there is less of a reason to expect racial diversity to be related to the number of nonprofits providing basic goods and services, and the results possibly show this. This finding also indicates the potential limitations of using an aggregated diversity index. Future studies should proceed with caution when using an index for variables like race or perhaps include categories of interest in regression models as separate variables alongside the total index. Additionally, neither of the proxy variables for resources – educational attainment and median housing value - were significant in the spatial models. The coefficient for the median housing value each year is very small, indicating a negligible impact. The choropleth map of median housing values can visually make sense of the coefficient's negative direction; the core Flint area in the center of the map has the lowest housing values and the largest cluster of nonprofits, but the areas surrounding the core metro area - especially to the north - also have lower values compared to the wealthier areas on the edges of the county.

Taken together, these results indicate that nonprofits providing basic goods and services are located in areas with higher needs, as indicated by the kernel and choropleth maps along with the spatial models showing the percent renting as a significant variable. Importantly however, these organizations are clustered in the core metro area of Flint. The surrounding tracts have comparable levels of needs, yet the density of nonprofits in these areas is much lower, possibly explaining some of the nonsignificant coefficients in the model. This finding echoes Yan et al., (2014) who found that nonprofits in the greater Hartford, Connecticut area are primarily located in urban areas with higher proportions of renters, as opposed to suburban or rural areas. The authors attributed this result to the fact that other organizations that these types of nonprofits work with, such as foundations, are located in urban downtown areas, along with potential zoning issues. That interpretation holds well in this study, too. For instance, two major foundations, the Charles Stewart Mott Foundation and the Community Foundation of Greater Flint., are both located in downtown Flint and are likely a key funder for many of the organizations included in this study. This may also shed light on the non-significance of the resource variables in the model. In theory, these types of nonprofits are likely aiming to be near those they serve, while at the same time staying close to resources for their continued financial viability. In the case of Genesee county and nonprofits in the Flint metro area, perhaps access to foundation resources and others downtown are enough to sustain their organizations, rather than household (i.e., individual) resources.

Limitations

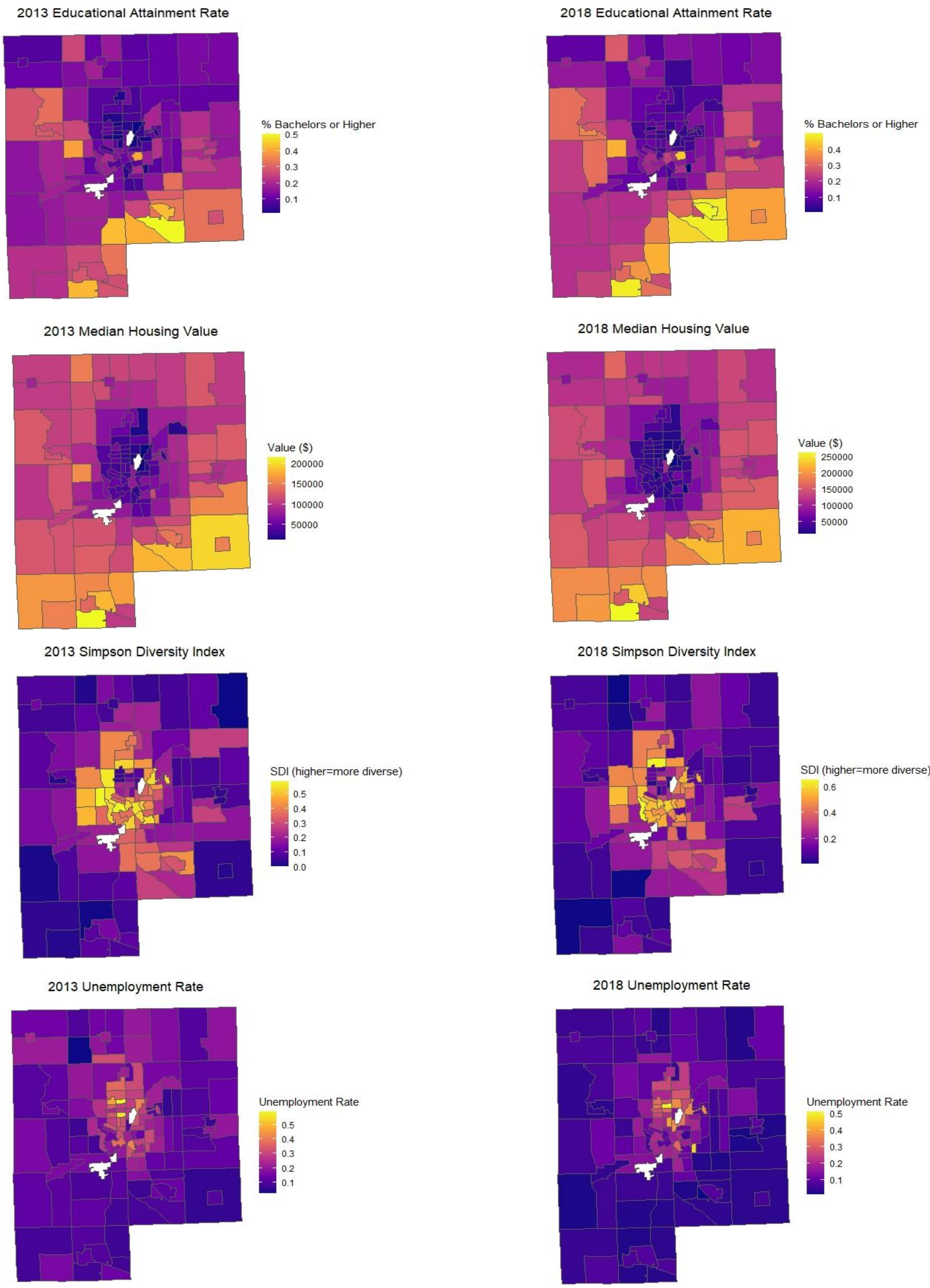
There are a number of limitations to this study. It is unfortunate that the agglomeration hypothesis was not able to be statistically tested due to modeling issues. As discussed above, the pattern observed in this study indicated evidence for some process of agglomeration, and a formal test would have provided further illuminating information. Methodologically, there are key aspects of this study that should be kept in mind. Nonprofit organizations were selected based on the authors criteria and NTEE codes; the critique from Fyall et al., (2018) of NTEE codes is noteworthy, and there were likely some organizations of interest to the study incidentally excluded. The dependent variable was constructed using kernel density estimation, which is sensitive to bandwidth selection; if future studies use this method, they could present a series of models with different bandwidth selections or include sensitivity analyses. Similarly, this study chose the census tract as the spatial level for analysis, but the results could have shifted, or a new pattern emerged were a different level chosen (e.g., census block group). Finally, the lack of data on government welfare provision also limits the extent of this study's conclusions. Were this data to become available, a fuller picture could emerge of areas where services are lacking.

Future Directions

The results of this study point toward a few different lines of work worth pursuing on the topic of nonprofits and service provision. First, a better measure for agglomeration economies in future studies would be of interest to the field, as this study indicates that some process of urban clustering is present. Second, future studies could use more advanced modeling approaches to provide richer details on the nonprofit sector. A spatial panel model approach similar to the one employed by Call and Voss (2016) for child poverty using the SPLM package in R (Millo & Piras, 2012) could account for temporal effects in nonprofit density. The difference between the OLS model results and the spatial models highlight the need to explicitly account for space in this research; a meta-analysis similar to Lu and Xu's (2018) could correct previous studies for the potential presence of spatial autocorrelation in prior studies. Lastly, future work should investigate whether zoning laws and NIMBYism ("Not in My Back Yard") in surrounding areas like Mount Morris, Burton, and Swartz Creek, may contribute to the pattern of urban clustering observed in this study. Suburban poverty is a well-recognized issue by scholars (see, for example, Kneebone & Berube, 2013) and if exclusionary zoning is what is prohibiting nonprofit organizations from operating in these areas, this would indicate a gap in services that deserves attention from community members and policy makers.

APPENDIX

Figure 5. *Choropleth Map for Model Variables*



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