Renters, Buildings, and Scale

A Spatial Analysis of Urban Tree Cover in Chicago

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Introduction

Cities are human constructions, planned and organized to suit human needs, wants, desires, and goals. As a consequence, when a tree appears in a long-established urban center, someone, at some point, made the decision to plant that tree. There is a natural aspect to that decision: trees grow best in sites with appropriate soil, light, and water. But there is also a human aspect: the decision to plant a tree reflects the values and priorities of landowners, present and past. The original landowner (or resident) had to want to plant a tree and subsequent landowners had to value the tree enough not to cut it down. Differences in financial priorities, resources, cultural values, and expected tenure in the neighborhood can all influence the decision to plant and maintain a tree, which produces the eventual variation in tree cover across a city.

Once in place, urban trees are not passive scenery. Beyond their role as habitat for birds and other animals, trees provide an array of essential ecosystem services: stormwater management (Berland et al., 2017), temperature control (Coseo & Larsen, 2014), air pollution reduction (Nowak et al., 2006), and carbon sequestration (Kendall & McPherson, 2012), among others. Although the general term *tree cover*, or *tree canopy cover*, is not a perfect proxy for what trees provide, because of different benefits related to age and species (Riley & Gardiner, 2020), places with more tree cover tend to have more of these benefits. Therefore, the uneven distribution of trees across a city can contribute to inequities among different neighborhoods and socioeconomic groups.

Recent research of urban tree distribution has focused on the relationship between homeownership and tree canopy cover. The landmark paper by Perkins et al. (2004) of a Milwaukee tree-planting program found a statistically significant positive correlation between homeownership and canopy cover at the census-tract level in residential neighborhoods and a corresponding negative correlation in census tracts with more renters. They suggest that two factors may produce this relationship: residential mobility (more transient renters are less likely to ever benefit from the trees they plant) and housing maintenance (renters probably do not invest in improvements that enhance property values and cause rents to rise). Other studies in various cities and at various spatial scales have corroborated an inverse correlation between rentership and tree cover (Heynen et al., 2006; Landry & Chakraborty, 2009; Koo et al., 2019). Scholars have, however, understudied the role of the built environment. Renters tend to live in neighborhoods with more paved surfaces and larger buildings that leave less space for planting trees; the observed relationship between renters and tree cover may merely be the product of renters living in neighborhoods with less space for trees. This paper addresses this gap in the literature by investigating the relationship between tree cover, rentership, and the built environment of Chicago.

A "traditional" model of Chicago, which uses socioeconomic indicators, will show a negative relationship between rentership and tree cover in Chicago, in line with the general academic consensus. In this study, however, I found that adding aspects of the built environment to the model, including single-family housing, age of housing, and use of public

transportation, erases the apparent relationship between rentership and tree cover. This finding indicates that the previously accepted explanations for the relationship between tree cover and rentership—residential mobility, housing maintenance, and the political influence of homeowners discussed by Landry and Chakraborty (2009)—have to be reevaluated in the light of this new evidence to account for other factors that influence the distribution of urban trees. While additional research is necessary to confirm that the observed relationship between rentership and tree cover is the product of land use, these results provide a preliminary indicator that previous explanations may not fully reflect all drivers of tree distribution. This has broad-ranging implications for urban tree-planting programs and other policy initiatives that seek to redress environmental inequities in urban environments.

Literature Review

Importance of the Urban Forest

The first and perhaps most obvious role of urban trees is to provide habitat for surrounding plants (Wittig & Becker, 2010) and animals, including birds (Parsons et al., 2006), cottontails (Abu Baker et al., 2015), ants (Yasuda & Koike, 2009), bats (Rhodes et al., 2006), squirrels (Merwe et al., 2007), and several other species (LaMontagne et al., 2015).

Second, urban trees contribute to human health. One such service is stormwater management. Tree canopies capture rain that would otherwise fall to the ground, mitigating the impact of heavy rainfall on sewer systems, and tree root networks loosen the soil, promoting water flow (Berland et al., 2017). Canopies and root networks also reduce nitrogen runoff that contributes to algal blooms in lakes, rivers, and ponds (Denman et al., 2006).

Third, trees help mitigate the "urban heat island" effect, which increases temperatures in urban areas compared to surrounding rural areas. After impervious surfaces (such as asphalt or concrete), tree canopy is the second most important variable for daily nighttime air temperatures in Chicago (Coseo & Larsen, 2014). Large-scale tree planting in Chicago could reduce citywide temperatures by up to 1.4°C (Akbari et al., 2001). This was a specific goal in Chicago's Climate Action Plan, which emphasized tree plantings by the Park District and the Bureau of Forestry (Coffee et al., 2010).

Fourth, urban trees reduce carbon emissions. In Chicago, trees planted adjacent to buildings can reduce energy demand by providing shade and wind deflection, resulting in a reduction of carbon emissions from 3.2% to 3.9% for buildings with 33% tree cover and from -0.2% to 3.8% with 11% tree coverage (Jo & McPherson, 2001). Urban trees can produce seasonal cooling-energy savings of up to 30% and heating-energy savings of 10% to 15% (Akbari et al., 2001). Carbon dioxide reduction through photosynthesis, though, is fairly minimal: in Chicago, the carbon stored in urban trees amounts to just 0.3% of citywide emissions (McGraw et al., 2010). The authors argue that tree-planting programs, despite this minor effect, could still be worthwhile, because they are deployed relatively easily and have significant additional benefits.

Fifth, urban trees increase residential and commercial property values. An early study in Athens, Georgia (Anderson & Cordell, 1988), demonstrated that a front-yard tree increased a house's sale price by approximately 1.1%. Subsequent studies, using a range of methodologies, have consistently found that urban trees increase property values. In Los Angeles, a novel model that controlled for spatial autocorrelation to evaluate the effect of "green cover" (determined by remote sensing) found that trees increased nearby housing prices substantially (Conway et al., 2010). A study using site-specific field measurement, rather than remote sensing, found that assessed property values increased on average by $1,586 per tree on a property (Escobedo et al., 2015). A hedonic price model[1] found that the number of street trees fronting a property increased home values (Donovan & Butry, 2010).

Finally, public opinion on urban trees is not driven substantially by any of these benefits. An extensive research survey found that urban residents value trees primarily for aesthetic and psychological benefits; while residents mentioned trees' role as wildlife habitat fairly often, they rarely mentioned property values and carbon storage (Peckham et al., 2013). Another research survey confirmed that aesthetic and psychological benefits play a strong role in shaping where people live: 75% of residents said trees on a property were important in selecting a home, and 77% said trees in a community were important in selecting a community (Zhang et al., 2007).

Spatial Inequities in the Urban Forest: The Case of Renters

Several studies have used spatial patterns to identify a relationship between tree cover and concentrations of low-income or minority residents. One of the oldest found a strong negative relationship between tree cover and the percentages of the non-white population and the poverty rate in New Orleans (Talarchek, 1990). Other work has found that high canopy cover correlates with higher levels of education and older housing stock (Heynen & Lindsey, 2003). The relationship between income, education, and dense tree cover was also observed in Brazil (Pedlowski et al., 2002) and Canada (Greene et al., 2018). Although these studies did not investigate the relationship between tree cover and homeownership specifically, they show that a neighborhood's tree cover can be influenced by its social and economic composition.

1. "Hedonic pricing is most often seen in the housing market, since real estate prices are determined by the characteristics of the property itself as well as the neighborhood or environment within which it exists" (Hargrave, 2021).

There is a well-established connection between high concentrations of renters and less tree cover, in part because rentership often correlates closely with the socioeconomic metrics used in other studies on this subject (Vlist et al., 2002). In Milwaukee's tree-planting program, for example, low homeownership correlated to low tree density (Perkins et al., 2004). A later work demonstrated that this relationship applied to residential canopy cover throughout Milwaukee, beyond the context of the city's planting program; the study concluded that renters, who move more frequently, may be less willing to plant trees and that landlords often see trees as maintenance nuisances and insurance liabilities (Heynen et al., 2006). In some cities, residential programs may simply exclude renters as a matter of course by requiring proof of homeowners' insurance (Ragsdale, 2012). A study in Tampa, Florida, of tree cover in residential rights-of-way confirmed the same mechanism identified in Perkins et al.; it concluded that homeowners understand the relationship of trees to property values and use their political influence to demand public tree planting in their neighborhoods (Landry & Chakraborty, 2009). The "opportunity cost" of trees on private land, which occupy ground that homeowners could otherwise use for a swimming pool or patio, means that they may see a higher net benefit from public trees than private ones (Pandit et al., 2013).

Several other studies have used various quantitative methods to measure the relationship between urban vegetation and renter-occupied housing. Remote sensing data and field observations of canopy cover and carbon storage potential show a negative correlation with the percentage of renters and no other neighborhood demographic indicators (Raciti et al., 2014). An innovative methodology—mapping street greenery through Google Street View—found a significant and positive association between owner-occupied units and vegetation (both private gardens and trees) (Li et al., 2016). A longitudinal study found that Atlanta's urban canopy has a consistently negative relationship with the proportion of renters in a neighborhood in both 2000 and 2013, even as the city's demographic makeup changed and the relationship between African American and Hispanic American populations and tree cover shifted from a negative to a positive correlation (Koo et al., 2019).

Some research suggests that historic demographic patterns also influence tree cover. Rates of owner-occupied housing in inner-city Baltimore correlated positively with yard stewardship and expenditures, but not tree stewardship, which suggests a "legacy effect": trees planted before white flight in the 1960s contribute to the present-day tree canopy (Troy et al., 2007). Later work, also in Baltimore, found that historic demographic patterns are more predictive of the current urban canopy than present demographics (Boone et al., 2010).

A handful of studies found no clear relationship between homeownership and tree cover, but unique characteristics explained the relationship in each case, and these are unlikely to apply to Chicago, the focus of this study. A positive correlation between renters and backyard vegetation in Montreal may be the product of the city's history as a "city of tenants," where home ownership is rarer than comparable North American cities; also, Montreal contains a unique mix of housing types where high-rises border owner-occupied detached houses surrounded by planted yards (Pham et al., 2013). The laws in some cities discourage homeowners from planting trees. For example, there is no significant relationship between owner-occupied housing and tree canopy in Portland, Oregon, where the municipal code states that the city owns all trees in rights-of-way but requires homeowners to maintain them (Ramsey, 2019). Home ownership and management duties for trees in the public right-of-way may vary between municipalities, streets, and even road segments, potentially explaining some variation between cities, though no study has examined this effect directly across multiple cities (Fischer & Steed, 2008).

Spatial Inequalities and Neighborhood Preferences

Grove et al. (2006) introduced the concept of neighborhood lifestyle characteristics to explain the finding that lifestyle behavior—not demographic variables—is the best predictor of tree cover on both private lands and public rights-of-way in Baltimore. These characteristics, developed for marketing, classify households into sixty-two consumer categories in an attempt to capture the complexity of American social class. Household land management decisions may be driven by a desire to "uphold the prestige of the household's neighborhood," suggesting that neighborhood inequalities may be the product of different values assigned to urban trees by different lifestyle groups (Grove et al., 2006, p. 592). Social class distinctions may explain seemingly counterintuitive results, such as the patterns in Philadelphia, where neighborhoods with more renters tended to have more tree canopy, except in areas of higher land values, where the relationship was reversed (Locke et al., 2016).

However, research that investigates the direct preferences of renters seems to contradict the idea that renters are less invested in the prestige of their neighborhoods. In New Haven, Connecticut, existing tree canopy displayed a moderately negative association with the percentage of renters, but requests for new trees came equally from all neighborhoods, including where renting is commonplace; this suggests that renters are at least as interested as homeowners in developing the canopies of their neighborhoods (Locke & Baine, 2015). Another survey found that both homeowners and renters felt overwhelmingly positive about having trees on their property, with no statistically significant difference between the two groups (Winter, 2017). A study in Portland, Oregon, found that both renters and homeowners were willing to pay more to live on a property with a nearby tree (Donovan & Butry, 2011). Survey research in a Toronto suburb "suggests that the factors associated with lower tree canopy in neighborhoods with low-income residents, renters, and large

minority populations may not be a result of reduced desire for trees or lower support for policies" (Conway & Bang, 2014, p. 242).

These studies indicate that some mechanism related to renting, beyond the lifestyle preferences identified by Grove et al. (2006), could be responsible for the observed differences in canopy cover between renters and homeowners. Opposition to urban forestry programs among renters may reflect concern about "green gentrification," where the development of environmental amenities threatens to raise property values, raise rents, and produce displacement (Dooling, 2009; Checker, 2011; Wolch et al, 2014). Anguelovski et al. (2019) and others have described this pattern, where environmental amenities burden established low-income residents, as an "environmental rent gap" (p. 1066). Although renters may have similar preferences as homeowners for urban vegetation, they may be suspicious of organized tree-plantings that are harbingers of higher rents and eventual displacement.

Large-scale displacement by green gentrification or an environmental rent gap appears unlikely, though, based on studies of the effect of trees on property values and rents. An assessment of a tree-planting program in Los Angeles found that an individual tree raised property values only $1,100 to $1,600 over the course of thirty-five years, less than $50 in added property values per year (McPherson et al., 2008). In Portland, Oregon, yard trees increased monthly rents by an average of $5.62 and adjacent public trees increased rents by around $21 (Donovan & Butry, 2011). While these small rental increases may affect some very low-income families, they would not result in large-scale displacement. Residential opposition can shape the distribution of some tree-planting programs (Carmichael & McDonough, 2018), but teasing out the relationship between past negative experiences with city tree maintenance, concerns about gentrification, and the renter-homeowner dynamic will require additional research.

The Urban Forest and the Built Environment

Pham et al. (2013) found that characteristics of the built environment, such as urban form and land-use types, were more important than demographics or local borough administration in determining urban vegetation. A study of four neighborhoods in suburban Toronto found that available planting space and resident attitudes correlate strongly with canopy cover and tree density, while the traditional suite of socioeconomic variables showed no significant relationship (Shakeel & Conway, 2014). Similarly, Jesdale et al. (2013) and Solecki et al. (2005) found that renters are more likely to live in areas with no tree cover and high impervious surfaces. Architectural styles also determine the physical availability of planting space (Ossola et al., 2019), and efforts to develop "green infrastructure" in Philadelphia were more difficult in neighborhoods with high rentership, due to both the program's structure and to properties that simply did not have room for vegetation, including street trees (Heckert & Rosan, 2016).

In summary, the existing literature shows a clear relationship between rentership and tree cover in a variety of urban areas: higher levels of tree cover, an important environmental amenity, are disproportionately present in areas with fewer renters. The mechanism behind this relationship, however, is uncertain. Some authors have suggested that this inequity results from characteristics unique to rentership, such as the higher mobility of renters, landlord reluctancy, or the impact of trees on property value or rents. A handful of studies have identified built form as an influential factor for this relationship: urban renters often live in areas where the built environment leaves little room for trees. My study aims to further investigate the relationship between rentership and the built environment. I will analyze the role of the built environment in shaping the relationship between renters and tree cover using neighborhood-level data on a number of aspects of the built environment in Chicago. The data I have selected—impervious acreage, auto dependence, walkability, housing size, house crowding, and housing-cost burden—have been used only rarely or never in past research, which will hopefully makes this study an important contribution to the current conversation.

Methodology

Study Area

The study area is the city of Chicago. While most other studies have assessed the distribution of urban trees at the census-tract or block-group level, I use the community area, a neighborhood-equivalent unit unique to Chicago, as my primary unit of analysis (Smith & Betancur, 2016). Chicago is divided into seventy-seven community areas, ranging in size from 1.61 km^2 to 27.71 km^2, with an average of 7.6 km^2 (see fig. 1). Researchers and government agencies have used community areas since the Local Community Research Committee at the University of Chicago defined them in the 1920s (Seligman, 2005; Smith & Betancur, 2016). The Chicago Department of Public Health, for example, presents its Chicago Health Atlas by community area, and the Department of Planning and Development's Green Healthy Neighborhoods defines its focus by specific South Side community areas. Community-area boundaries often reflect socioeconomic barriers that divide Chicago: in 2010, only around a third of community areas qualified as "integrated," and area boundaries often correspond to unofficial neighborhood boundaries (Emmanuel et al., 2017). By conducting my analysis at a scale that approximates local neighborhoods, I am able to examine the urban forest at the scale associated with New Urbanism principles of city planning (Talen, 2005). Furthermore, by using a locally meaningful definition of community, I am able to present my findings in a way that will resonate with local policymakers and residents.

In order to ensure that the relatively large unit of the community area

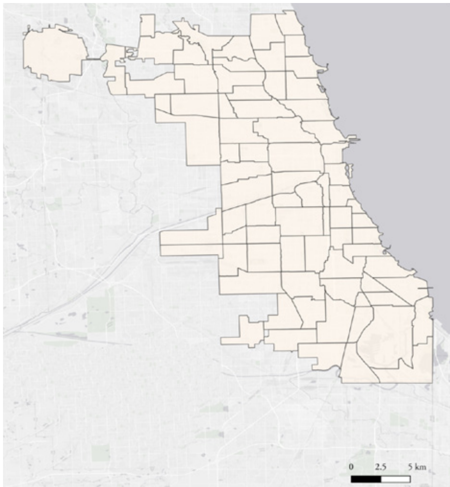


Figure 1: Chicago Community Areas (Chicago Data Portal, n.d.)
Map made by author using QGIS.

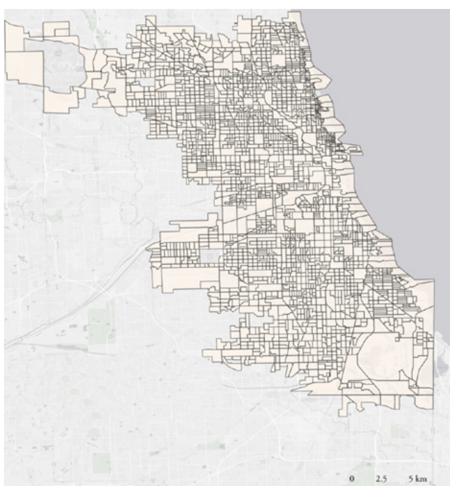


Figure 2: Chicago Census-Block Groups (US Census Bureau, 2021)
Map made by author using QGIS.

does not miss important distinctions that occur at a finer scale (Locke et al., 2017), I replicated my procedure at the census block-group level for all block groups (2,335) that overlap the city of Chicago (see fig. 2). Block groups range in area from 0.004 km^2 to 17.74 km^2, with an average of 0.30 km^2.

Data

This paper relies on the Chicago regional land-cover dataset produced by the University of Vermont's Spatial Analysis Laboratory (SAL) (Chicago Regional Land Cover Dataset, 2016). This data is the most detailed and accurate land-cover dataset for Cook County. It uses LiDAR[2] and high-resolution imagery (1 m^2) from a range of years to classify the entire study area into seven categories: tree canopy, vegetation (foliage under ten feet), bare soil, water, buildings, roads/railroads, and other paved surfaces. Tree canopy overhanging other classes was assigned to the tree canopy category. For every community area and block group, I calculated the percentage of land area covered by tree canopy using the SAL's Tree Canopy Assessment Tool in ArcGIS.[3]

At the community-area scale, I draw almost all demographic, housing, land use, and other variables from the Community Data Snapshots prepared by the Chicago Metropolitan Agency for Planning (CMAP, n.d.). I used the November 2018 release, as it includes data through 2016, the year the land-cover dataset was published. I draw the underlying data primarily from the 2012–16 American Community Survey (ACS) 5-Year Estimates, which CMAP prepared by aggregating ACS estimates from the census-tract and block-group levels to the community-area

2. LiDAR (Light Detection and Ranging) "allow scientists and mapping professionals to examine both natural and manmade environments with accuracy, precision, and flexibility" (NOAA, 2021).

3. ArcGIS is a software used to create maps and to analyze demographic and lifestyle data (Esri, 2021a).

level. When possible, I attempted to use data collected in the year 2016 in order to avoid the uncertain geographic context problem (Kwan, 2012a; Kwan, 2012b). CMAP prepared two additional variables from sources other than census data: it calculated annual vehicle miles traveled per household, a metric of automobile dependency that serves as a proxy for automobile-oriented land-use patterns, using data from the ACS, the Illinois Environmental Protection Agency, and the Illinois Secretary of State; it calculated open space per one thousand residents from ACS data and its own land-use inventory. This data allows me to account for variation in community-area demographics and to investigate which of these demographic variables are correlated with tree cover and health. The City of Chicago's Health Atlas provided three additional variables: individual poverty rate, the percentage of residents living in crowded housing, and the percentage of residents paying more than 35% of their income on housing (Chicago Health Atlas, n.d.). The city calculated these variables at the community-area level from the ACS 5-Year Estimates for 2012–16.

I joined the data discussed above to a shapefile[4] of Chicago's community areas downloaded from the City of Chicago's Data Portal (Chicago Data Portal, n.d.). I then added the land-use percentages, which I calculated from the Chicago regional land-cover dataset for each community area, using the University of Vermont's Tree Canopy Assessment Tool in ArcGIS, to produce a single file containing all metrics of tree distribution and demographic variables by community area.

I replicated this procedure at the block-group level, using 2012–16 ACS 5-Year Estimates for all variables included at the community-area level, with the exception of open space per one thousand and average vehicle miles traveled, which the ACS does not track. I used the SAL land-cover dataset to calculate impervious acres per household. I joined

4. "A shapefile is a simple, nontopological format for storing the geometric location and attribute information of geographic features" (Esri, 2021b).

this data to the 2016 TIGER/Line shapefile[5] of all 2,325 populated block groups partially or entirely within the city of Chicago, then added the land-use percentages.

I selected socioeconomic and built-environment variables based on their use in previous work on the topic and evidence of some association with urban tree cover (see tables 1a & 1b). I drew all socioeconomic variables from prior studies that used the same or similar variables. I have added several novel variables in the built-environment variables (impervious acreage, auto dependence, walkability, housing size, house crowding, and housing-cost burden) that reflect aspects of housing and transportation not present in prior studies on the topic. I include descriptive statistics for all variables at the community-area (CA) and block-group (BG) level (see tables 2a & 2b).

Regression Diagnostics and Analysis

I used the software GeoDa (version 1.14.0.10) to perform a three-step process.

Step 1: I conducted two ordinary least squares (OLS) regressions, one using the covariates in Table 1a and the other using the covariates in Tables 1a and 1b. The percentage of tree canopy cover was the dependent variable in both cases, producing a basic understanding of how the various covariates in each community area or block group related to the canopy cover in that block group.

Step 2: I removed errors by testing for spatial autocorrelation. Spatial autocorrelation occurs when values at certain locations are more similar to (or different from) nearby values than a random distribution would

5. TIGER/Line shapefiles are "extracts of selected geographic and cartographic information from the U.S. Census Bureau's Master Address File/Topologically Integrated Geographic Encoding and Referencing (MAF/TIGER) database" (U.S. Census Bureau, 2021).

produce, violating the assumption of independent observations used in standard models; in other words, if neighborhoods with many trees tend to border neighborhoods that also have many trees, spatial autocorrelation is present. Failure to identify and account for spatial autocorrelation can produce inaccurate regression estimates and higher standard errors (Schwarz et al., 2015), which can influence the results of studies like this one: Duncan et al. (2014) found that an OLS regression indicated a significant inverse relationship between African American neighborhoods and tree density in Boston, but, once they accounted for spatial autocorrelation, no significant relationship remained. I used a Moran's I test to test for spatial autocorrelation. If the Moran value is near zero, there is little or no spatial autocorrelation; a value close to -1 suggests that areas with large and small values of canopy cover are likely to be neighbors; and a value close to 1 suggest that adjacent neighborhoods are likely to have similar tree cover.

Step 3: If spatial autocorrelation is present, then I use the variables in the original OLS regression in a new spatial autoregression model, as described in Anselin (2005) (see the appendix for more detail). By controlling for spatial dependence, I can improve the model fit and generate a model that does not violate the assumption that observations are independent. In both cases, I used a queen's contiguity spatial weights matrix with one order of contiguity, which treats community areas as neighbors if they share a boundary or a corner.

Results

Regression Output

An ordinary least squares (OLS) regression, considering all socioeconomic covariates in Table 1a with canopy cover as the dependent variable, displayed substantial spatial dependence, with a remarkably high Moran's I value of 5.45 ($p<0.001$). The Lagrange multiplier tests for lag

($p=0.00005$) and error ($p=0.00018$) are both significant, which provides further confirmation that spatial dependence is present in the data. The robust Lagrange multiplier test for lag is not as significant ($p=0.12$), but substantially more significant than the robust Lagrange multiplier test for error ($p=0.70$), both of which suggest that adding a spatially lagged dependent variable will do more to correct for spatial dependence than adding a spatially lagged error term. In particular, the results of the robust Lagrange multiplier test for error suggests that most of the error dependence detected in the simple LM test would be addressed through a spatial lag model. The Lagrange multiplier test for a spatial autoregressive moving average (SARMA) is also significant ($p=0.00027$), but less so than either the standard LM-lag or LM-error tests. It is likely that the LM-SARMA statistic is simply detecting the need for a spatial lag or error model, rather than suggesting the need for a higher-order model (Elhorst, 2010). Using the decision rules from Anselin (2005), these results suggest that adding a lag dependent variable would address the error dependence. As a result, this paper relies on a spatial lag model (SAR_{lag}) in order to control for spatial dependence.

Table 3 shows the regression result of two models: the SAR_{lag} model with canopy cover as the dependent variable, considering only the demographic variables used in prior literature (the "socioeconomic model"), as well as a SAR_{lag} model that incorporates additional variables that reflect characteristics of the built environment (the "combined model").

The results of the demographic model indicate that, of the variables tested, only rentership and four-year college education display any significant association with urban tree cover. Based on the literature, these results make sense: education tends to correlate positively with tree cover, while rentership tends to correlate negatively, both confirmed in these results. Once I added the built-environment variables from Table 1b, however, foreign-born population, poverty rate, and median age also display a significant association with tree cover, as do work commutes via modes other than single-occupancy vehicle (carpool, public transit, bicycle, or on foot), crowded housing rate, housing-cost burden, median number of rooms, and the percentage of single-family homes. The increase in R-squared and log-likelihood values and decrease in the AIC and Schwarz criterion also demonstrate that the combined model is a better fit. The lower, less significant value of the Breusch-Pagan test also indicates that heteroskedasticity is less of a problem in the combined model. The relatively large coefficient for *rho* in the demographic model indicates that the spatial lag term may be standing in for other important variables, while the much smaller coefficient in the combined model suggests at least some of those variables have been addressed in the new model.

Figure 3 displays how this relationship functions spatially: the map of rentership on the left looks fairly similar to the map of non-single-occupancy vehicle commutes on the right. Areas where few people rent are also areas where the largest percentage of people commute by single-occupancy vehicle, and, as Figure 4 displays, these are also the areas with the most tree cover. This relationship, however, only goes so far: while the significance of the built-environment variables confirms the hypothesis that these variables could explain a significant amount of the variation in tree cover, it is difficult to speculate why age and foreign-born percentage are also significant in the combined model. Notably, several demographic variables often used in past research, including race, income, and population density, displayed little relationship to canopy cover in either model, though this may simply be the result of the small sample size of seventy-seven community areas. Similar past studies have relied on larger samples: Koo et al. (2019) included 288 block groups in their study of Atlanta, Duncan et al. (2014) used 167 census tracts in their study of Boston, and Ramsey (2019) used 442 block groups in his study of Portland, Oregon.

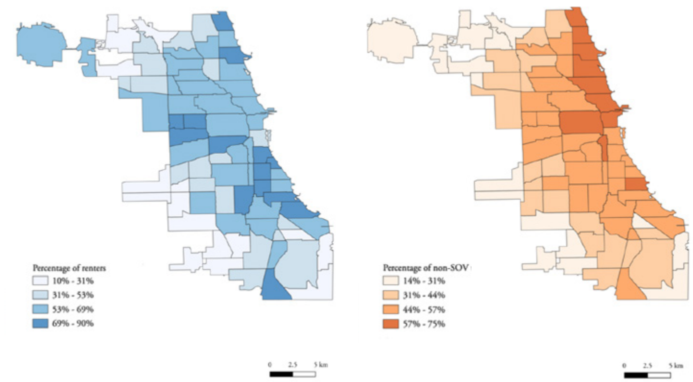


Figure 3: Rentership and Trips by Non-Single-Occupancy Vehicle, both by Community Area
Maps made by author using QGIS, Jenks natural breaks classification (n=4), and colors from colorbrewer2.org.

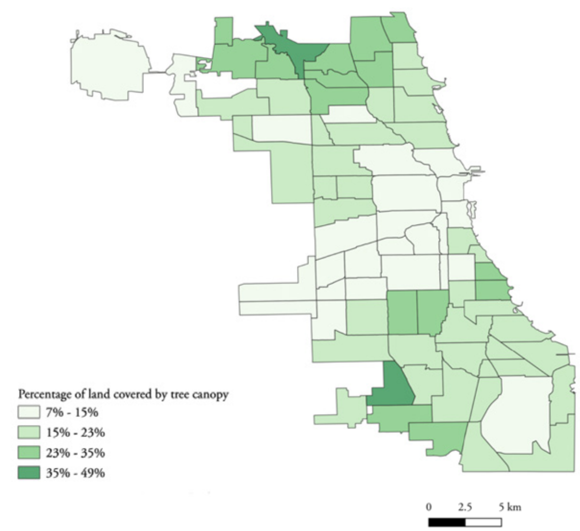


Figure 4: Canopy Cover by Community Area
Map made by author using QGIS, Jenks natural breaks classification (n=4), and colors from colorbrewer2.org.

Scale Sensitivity

The aggregation to the community-area level (as well as the small sample size) may have masked important variation that explains the relatively low number of significant variables and the lack of significance for race, income, and population density in the community-area model. The boundaries of community areas, while based on community boundaries determined by sociologists, are ultimately arbitrary units, which raises the possibility of ecological fallacy problems (Openshaw, 1984). In order to test this, the procedure was replicated at the block-group level, the smallest geographic unit for which most of the data used was available, using the 2,325 populated block groups that overlap with the boundaries of the city of Chicago.[6] The only modification to the procedure described in the methodology was the use of a spatial weights matrix with two orders of contiguity rather than one to account for the smaller scale of block groups. An OLS regression, considering all covariates in the combined model with canopy cover as the dependent variable, displayed substantial spatial dependence (Moran's I=28.6, $p<0.001$). The Lagrange multiplier tests for lag ($p<0.00001$) and error ($p<0.00001$) are both significant, indicating that spatial dependence is present. The robust LM test for lag ($p<0.00001$) and error ($P=0.00002$) are both highly significant, as is the Lagrange SARMA ($p<0.00000$); though the difference between the two is extremely slight, the results of the robust tests suggest using the SAR_{lag} model.

Table 4 shows the regression results of the demographic model at the block-group level. It confirms the significance of rentership and bachelor's degree attainment in determining local tree cover. Additionally, several new variables—population density, foreign-born percentage,

6. I intended to replicate this procedure using census tracts, but I lost access to the University of Chicago Library's computers with ArcGIS as a result of the 2020 coronavirus pandemic.

linguistic isolation, median age, unemployment rate, and several racial variables—show a significant relationship to tree cover. Also notable are the high results for the Breusch-Pagan test, suggesting heteroskedasticity in the model, and the likelihood ratio test, suggesting that the introduction of the spatial lag term has not fully controlled spatial effects.

As in the community-area model, adding the transportation and housing variables changes the model dramatically. Several of the housing variables—housing age, single-family housing, number of rooms, median house value, and impervious surfaces per capita—are highly significant, the R-squared is significantly better, and the improvements to the log likelihood, AIC, and Schwarz criterion are all relatively apparently. The Breusch-Pagan test and likelihood ratio test, however, remain highly significant, suggesting that the additional variables have not addressed all of the underlying sources of misspecification. Additionally, the fairly large value of the coefficient of *rho* in both models suggests that unmeasured important variables may continue to exist that are not captured in the model.

Discussion

Previous studies have observed that neighborhoods with a higher proportion of renters correlate with lower tree canopy cover (Heynen et al., 2006; Koo et al., 2015). One theory is that renters are less motivation to plant and steward trees, because they move more than homeowners and are less likely to reap the benefits of a tree that may take twenty years to grow; further, homeowners may exert political influence to demand public tree planting, because trees raise property values (Landry & Chakraborty, 2009). Renters, by contrast, would oppose higher property values that are passed on in the form of higher rents and eventual displacement (Wolch et al., 2014).

My study of Chicago appears initially to support findings in the past literature: rentership has a strong negative correlation with tree canopy. In the model of tree cover containing only demographic variables, rentership stands out: along with education, it is the only variable with a significant relationship to tree cover ($p<.05$). However, once variables reflecting the built environment—auto dependency, age and composition of housing stock, and neighborhood-level open space—are added to the model, the relationship flips: rentership demonstrated a significant and positive correlation with canopy cover, and the overall explanatory power of the model increases. The higher R-squared, higher log likelihood, lower AIC value, and lower Schwartz criterion all indicate a much better model fit for the combined model relative to the demographic model.

Several of the variables associated with higher tree canopy cover—percentage of single-family homes, size of dwelling units, and vehicle miles traveled—are typical features of more suburban-style residential areas with fewer multiunit buildings and less mass transit. This relationship between canopy and variables associated with low density supports the hypothesis that rentership itself is not the variable that determines areas of low tree cover, but rather the product of renters disproportionately living in dense areas with many multiunit buildings, where land use allows less space for vegetation. This finding agrees with findings that urban form and land-use type are the most important factors in determining urban vegetation (Pham et al., 2013) and that found property characteristics and resident attitudes are more significant in determining canopy cover than a traditional suite of socioeconomic variables (Shakeel & Conway, 2014).

However, these results do not fully support the hypothesis from studies of urban New Jersey (Jesdale et al., 2013) and nationwide (Solecki et al., 2005) that renters tend to live in areas of high impervious surfaces where trees cannot grow. Impervious surface area per capita did not appear significant in the community-area model, but it was highly significant in the block-group model. In the community-area model, variables related specifically to housing, such as the percentages of homes built before 1940 and of single-family homes, had a significant positive relationship with higher tree cover. These results suggest that impervious surfaces do not provide a full explanation for areas of low tree cover, at least not at the large spatial scale of community areas. Instead, considering the impacts of residential built form and transportation networks is essential to understanding patterns of tree canopy cover in urban environments.

The results at the block-group level demonstrate a similar pattern, with some additional caveats. While rentership displays the same flip from a negative to a positive coefficient, it is not at all significant in the combined model; instead, a variety of additional demographic variables are significant in both the demographics-alone and the combined model. Additionally, while the R-squared demonstrates a similar improvement, the other statistical tests indicate that the additional variables do not fully address the heteroskedasticity and spatial effects that may be affecting the model. While the initial results at the community-area level present a nice and clear-cut verdict on the importance of built-environment variables in the relationship between renters and tree canopy cover, the block-group results suggest that further investigation of all the contributing aspects to this relationship is needed. Some of the difference between the community-area and block-group results is likely explained by the modifiable areal unit problem (MAUP): correlations that appear pronounced when using geographically larger units can often vary substantially at smaller scales (Fotheringham & Wong, 1991).

Limitations

A limitation of this study is the lack of historical data, which prevents a comprehensive test of the "legacy effect" (Troy et al., 2007; Boone et al., 2010). Some historical statistics, such as race, are available from the decennial census at the community-area level, but more complex modeling of "lifestyle clusters" (Boone et al., 2010), such as historic data on home values, incomes, occupations, and education levels, was beyond the scope of this paper. I would need to do additional testing of historic demographic variables to rule out fully any "legacy effects" in the results.

Another limitation is the lack of any policy data. Past research has demonstrated that municipal ordinances and other legal measures to encourage the growth of tree cover can have a substantial impact (Landry & Pu, 2009). It is possible that programs at the neighborhood or ward level in Chicago could account for some of the apparent differences across the city, but it was not possible to model these programs and their effects in this paper.

Finally, the results of the block-group analysis show that neither the OLS regression nor the SAR_{lag} model captures all the variables influencing the distribution of tree canopy adequately. One possible explanation is that I need to consider other influential variables or that a more sophisticated regression would better account for spatial effects. It is possible that both may be necessary to produce a regression that closely matches the actual distribution of tree canopy at the block-group level, which opens an extensive avenue for further research.

Conclusions

Urban trees deliver important benefits to nearby residents, including pollution reduction, energy savings, and stormwater and noise control. Ensuring that this environmental amenity is distributed equitably is an important consideration for city planners, particularly given the history of other environmental inequities in cities generally (Downey, 2007) and Chicago specifically (Pellow, 2002; Hardy, 2017). The literature on the current distribution of urban trees is substantial and shows consistently that trees are distributed unevenly among socioeconomic groups across many cities (Talarchek, 1990; Pedlowski, 2002; Heynen et al., 2006; Landry & Chakraborty, 2009; Koo et al., 2019). Many of these studies identified renters as a group that would naturally be associated with fewer trees.

None of those studies, however, considered the array of built-environment variables included in this study. When those variables are included, the relationship between renters and tree cover disappears or reverses. It appears that *renters* do not prefer Chicago areas without trees, rather they just happen to live in the kinds of *built environments* that typically lack trees. These results suggest that future research into urban environmental inequities should attempt to account for the history and development of the city; older, more densely populated urban areas tend to have less tree cover than suburban-style developments on the outskirts of the city. Current environmental inequities, in other words, may have less to do with the people living in the city today and more to do with land-use decisions made more than a century ago, which should influence the strategies used to redress those inequities.

This study also highlights the importance of scale in future research. Most studies of urban tree cover have relied on census tracts or block groups. These may miss features of the relationship between urban trees and people that only become apparent when using spatial units, such as community areas in Chicago that mirror how local residents define their own neighborhoods. At the same time, municipalities and local nonprofits interested in addressing these issues should take care to account for important relationships that are not apparent at the neighborhood level, but can be detected at smaller spatial scales like the block-group level. Ultimately, these results highlights the need for additional research into the relative influence of the built environment in determining the spatial distribution of environmental amenities, as well as the implications of that distribution for strategies to address distributional inequities. ❍

Table 1a. Socioeconomic Variables

Description	Previous Studies Using Variable	Source
Rentership (%)	Koo et al., 2019; Landry & Chakraborty, 2009; Landry & Pu, 2010; Li et al., 2016; Locke & Baine, 2015; Perkins et al., 2004; Pham et al., 2013, Ramsey, 2019; Riley & Gardiner, 2020; Shakeel & Conway, 2014	2012–16 ACS (CMAP)
Median age	Landry & Chakraborty, 2009; Landry & Pu, 2010; Shakeel & Conway, 2014	2012–16 American Community Survey (ACS) 5-Year Estimates (prepared by CMAP at the community-area level)
African American (%)	Duncan et al., 2014; Koo et al., 2019; Landry & Chakraborty, 2009; Li et al., 2016; Perkins et al., 2004; Ramsey, 2019	2012–16 ACS (CMAP)
Asian American (%)	Koo et al., 2019; Ramsey, 2019; Shakeel & Conway, 2014	2012–16 ACS (CMAP)
Hispanic American (%)	Duncan et al., 2014; Koo et al., 2019; Landry & Chakraborty, 2009; Landry & Pu, 2010; Li et al., 2016; Ramsey, 2019	2012–16 ACS (CMAP)
White (%)	Landry & Pu, 2010; Li et al., 2016; Locke & Baine, 2015; Ramsey, 2019	2012–16 ACS (CMAP)
HS diploma or higher	Locke & Baine, 2015; Ramsey, 2019	2012–16 ACS (CMAP)
Bachelor's degree or higher	Conway, 2014; Li et al., 2016; Pham et al., 2013; Riley & Gardiner, 2020; Shakeel & Ramsey, 2019	2012–16 ACS (CMAP)
Median household income ($)	Greene et al., 2018; Landry & Chakraborty, 2009; Locke & Baine, 2015; Perkins et al., 2004; Pham et al., 2013; Ramsey, 2019; Riley & Gardiner, 2020	2012–16 ACS (CMAP)
Unemployment rate (%)	Ossola et al., 2019	2012–16 ACS (CMAP)
Poverty rate (%)	Duncan et al., 2014; Koo et al., 2019; Riley & Gardiner, 2020	2012–16 ACS (Chicago Health Atlas)
Population density (per km^2)	Duncan et al., 2014; Locke & Baine, 2015; Ramsey, 2019; Pham et al., 2013; Riley & Gardiner, 2020	2012–16 ACS (CMAP)
Foreign born (%)	Pham et al., 2013	2012–16 ACS (CMAP)
Linguistic isolation (%)	Pham et al., 2013 (as "recent immigrants")	2012–16 ACS (CMAP)

Table 1b. Built-Environment Variables

Description	Previous Studies Using Variable	Source
Pre-1940 built homes (%)	Koo et al., 2019; Landry & Chakraborty, 2009; Landry & Pu, 2010; Pham et al., 2013; Ramsey, 2019; Shakeel & Conway, 2014	2012–16 ACS (CMAP)
Detached single-family homes (%)	Landry & Pu, 2010; Pham et al., 2013; Shakeel & Conway, 2014	2012–16 ACS (CMAP)
Median number of rooms		2012–16 ACS (CMAP)
Median house value	Landry & Pu, 2010	2012–16 ACS (CMAP)
Vacancy rate (%)	Heynen et al., 2006; Landry & Pu, 2010	2012–16 ACS (CMAP)
Severe (35%+) housing-cost burden (%)		2012–16 ACS (CHA)
Crowding: >1 person per room (%)		2012–16 ACS (CHA)
Impervious area per household (m^2)	Heckert & Rosan, 2016	UVM SAL
Open space per 1,000 residents (acres)	Duncan et al., 2014; Heckert & Rosan, 2016; Pham et al., 2013; Shakeel & Conway, 2014	CMAP
Non-single-occupancy-vehicle (SOV) commutes		2012–16 ACS (CMAP)
Average vehicle miles traveled (VMT)		CMAP

Table 2a. Socioeconomic Descriptive Statistics

	Mean		Standard Dev.		Min		Max	
Variable Description	CA	BG	CA	BG	CA	BG	CA	BG
Tree canopy cover (%)	19.19	20.01	7.20	8.53	7.27	0.59	48.78	76.20
Rentership (%)	52.83	52.26	19.05	24.48	9.82	0	89.58	100.00
Median age	35.41	36.24	4.80	8.40	21.30	13.9	47.12	85.40
African American (%)	38.25	34.73	39.59	40.59	0.47	0.00	99.06	100.00
Asian American (%)	5.99	5.12	10.71	9.77	0.00	0.00	75.18	97.11
Hispanic American (%)	26.07	25.99	28.14	29.79	0.00	0.00	92.62	100.00
White (%)	27.94	32.71	27.24	31.64	0.38	0.00	88.66	100.00
HS diploma or higher (%)	82.05	82.87	10.71	13.74	50.36	30.81	98.39	100.00
Bachelor's degree or higher (%)	30.27	32.92	21.25	25.59	5.00	0	82.77	99.33
Median household income ($)	48,931	54,795	22,166	31,781	14,287	0	108,146	207,969
Unemployment rate (%)	13.65	12.67	8.08	11.07	3.22	0	36.93	91.58
Poverty rate (%)	22.98	21.44	12.21	16.15	1.60	0	65.8	92.79
Population density (per km^2)	5,018	7,905	2,676	9,126	380	58	12,330	25,3318
Foreign born (%)	20.38	18.93	15.94	16.68	0.88	0	62.33	96.15
Linguistic isolation (%)	13.95	8.48	13.03	10.56	0.36	0	53.11	66.18

Table 2b. Built-Environment Descriptive Statistics

	Mean		Standard Dev.		Min		Max	
Variable Description	CA	BG	CA	BG	CA	BG	CA	BG
Tree canopy cover (%)	19.19	20.01	7.20	8.53	7.27	0.59	48.78	76.20
Pre-1940 homes (%)	41.25	44.70	31.76	25.72	1.40	0	83.38	99.14
Detached single-family homes (%)	33.67	33.75	25.59	30.48	1.87	0	88.17	100.00
Median number of rooms	5.44	4.99	0.74	0.96	3.72	0	7.20	9.00
Median house value ($)	21,3351	24,2221	94,392	151,417	56,875	0	488,678	1,104,200
Vacancy rate (%)	13.20	12.67	6.88	10.40	4.75	0.00	35.44	70.00
Severe (35+%) housing-cost burden (%)	37.09	44.08	9.14	23.28	14.6	0.00	56.00	100.00
Crowding: >1 person per room (%)	4.37	4.31	2.99	5.53	0.50	0.00	14.30	
Impervious area per capita (m^2)	153.50	142.28	138.30	335.18	48.41	3.69	1051.55	11949.05
Open space per 1000 residents (acres)	2.91	n/a	2.83	n/a	0.02	n/a	15.59	n/a
Non-SOV commutes (%)	44.16	44.25	13.24	18.47	14.16	0.00	75.34	100.00
Average vehicle miles traveled (VMT)	12,639	n/a	3,974	n/a	6,581	n/a	31,817	n/a

Table 3. SAR_{lag} Model Results for Canopy Cover at the Community-Area Scale

Variable	Coefficient	Standard error	z value	Coefficient	Standard error	z value
Rho	0.483***	0.111	4.35	0.0952	0.0951	1.00
Constant	122	99.8	1.22	-196*	80.6	-2.43
Rentership	-28.3**	9.03	-3.14	62.9***	13.7	4.58
Median age	0.135	0.260	0.520	0.529*	0.21	2.56
African American	-104	97.3	-1.07	68.4	71.5	0.957
Asian American	-124	93.6	-1.33	67.1	71.6	0.937
Hispanic American	-110	94.3	-1.17	70.9	71.1	1.00
White	-99.0	97.1	-1.02	78.6	71.5	1.10
HS diploma	-13.5	21.6	-0.625	4.68	15.8	0.295
Bachelor's degree	28.8*	11.6	2.49	58.4***	9.65	6.05
Median income	-0.000104	0.000115	-0.902	6.05e-05	0.000101	0.600
Unemployment rate	2.96	18.2	0.163	19.6	13.2	1.49
Poverty rate	0.378	0.209	1.81	0.299*	0.146	2.04
Population density	-0.000135	0.000319	-0.424	-0.000174	0.000348	-0.500
Foreign born	-21.2	19.5	-1.09	45.9**	16.3	2.82
Linguistic isolation	35.7	33.4	1.07	-35.5	24.2	-1.47
Pre-1940 homes				6.48	4.41	1.47
Detached single-family homes				38.5***	9.95	3.87
Median number of rooms				8.48***	1.90	4.46
Median house value				-2.22e-05	1.81e-05	-1.23
Vacancy rate				-8.84	13.3	-0.664
Housing-cost burden				0.272**	0.129	2.11
Crowding				0.649**	0.331	1.96
Impervious area				-0.00679	0.00662	-1.03
Open space per 1000				0.293	0.209	1.40
Non-SOV commutes				-30.7**	10.3	-2.97
Average VMT				-0.000181	0.000284	-0.638
Community areas	77			77		
R-squared	0.535			0.835		
Log likelihood	-234			-192		
Akaike information criterion	500			438		
Schwarz criterion	538			501		
Breusch-Pagan test	85.4***			37.0		
Likelihood ratio test	14.9***			0.949		

*p<0.05, **p<0.01 ***p<0.001

Table 4. SAR_{lag} Model Results for Canopy Cover at the Block-Group Scale

Variable	Coefficient	Standard error	z value	Coefficient	Standard error	z value
Rho	0.701***	0.0304	23.0	0.339***	0.0223	15.2
Constant	1619.02***	5.09	3.73	35.9***	3.70	9.70
Rentership	-3.51***	0.835	-4.20	1.73	0.890	1.94
Median age	0.0392	0.0208	1.89	0.0376*	0.0148	2.54
African American	-11.0*	4.59	-2.39	-7.48*	3.10	-2.41
Asian America	-14.4**	4.92	-2.93	-9.18**	3.33	-2.76
Hispanic American	-11.9**	4.56	-2.61	-7.91*	3.09	-2.56
White	-10.6*	4.61	-2.29	-7.50*	3.12	-2.41
HS diploma	-3.58	1.91	-1.87	-2.61*	1.33	-1.97
Bachelor's degree	4.82***	1.17	4.13	6.12***	0.900	6.81
Median income	5.48e-06	7.71e-06	0.711	-1.74e-06	5.58e-06	-0.312
Unemployment rate	4.91**	1.48	1.30	2.99*	1.27	2.35
Poverty rate	1.32	1.33	0.99	-0.330	1.05	-0.315
Population density	-9.70e-05***	1.69e-05	-5.75	8.86e-05***	1.21e-05	7.30
Foreign born	-5.47**	1.90	-2.88	-1.83	1.32	-1.39
Linguistic isolation	5.73*	2.36	2.43	4.31**	2.07	2.74
Pre-1940 homes				3.4.37***	0.488	8.95
Detached single-family homes				3.60 ***	0.710	5.07
Median number of rooms				0.478*	0.195	2.45
Median house value				4.55e-06***	9.70e-07	4.70
Vacancy rate				1.02	1.12	0.913
Housing-cost burden				0.0374	0.484	0.0772
Crowding				-0.286	2.17	-0.132
Impervious area				-0.450***	0.00914	-49.3
Non-SOV commutes				2.36***	0.715	3.30
Number of observations	2,325			2,325		
R-squared	0.383			0.719		
Log likelihood	-7766			-6814		
Akaike information criterion	15564			13679		
Schwarz criterion	15656			13822		
Breusch-Pagan test	255***			1326***		
Likelihood ratio test	648***			251***		

*p<0.05, **p<0.01 ***p<0.001

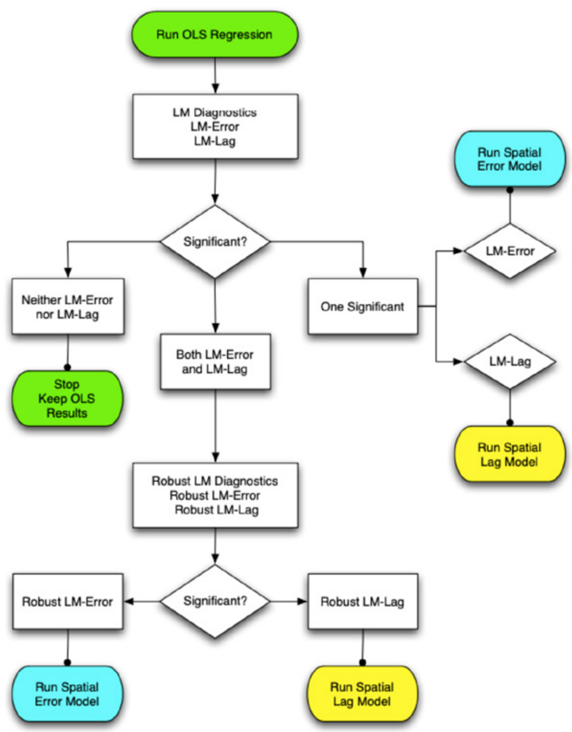
Note: The 2012–16 ACS 5-Year Estimates, which form the basis of this table, did not include open space per capita and average vehicle miles traveled, which explains their absence here.

Appendix

GeoDa provides five variations of Lagrange multiplier tests to identify whether spatial autocorrelation is present in an OLS regression and, if the answer is yes, whether the problem can be best addressed by adding a spatially lagged dependent variable or a spatial autoregressive error term, following the decision process depicted below (Anselin, 2005).

The simple Lagrange multiplier tests for lag and error test for a spatially lagged dependent variable and a missing error term, respectively, while the robust forms of each test for a missing lagged dependent variable in the possible presence of error dependence, and vice versa, respectively.

Spatial Regression Decision Process (Anselin, 2005)



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