



# Is Planting Equitable? An Examination of the Spatial Distribution of Nonprofit Urban Tree-Planting Programs by Canopy Cover, Income, Race, and Ethnicity

Shannon Lea Watkins<sup>1</sup>, Sarah K. Mincey<sup>2</sup>,  
Jess Vogt<sup>3</sup>, and Sean P. Sweeney<sup>2</sup>

## Abstract

This article examines the spatial distribution of tree-planting projects undertaken by four urban greening nonprofit organizations in the Midwest and Eastern United States. We use a unique data set of tree-planting locations, land use data, and socioeconomic information to predict whether a census block group ( $n = 3,771$ ) was the location of a tree-planting project between 2009 and 2011. Regression results show tree-planting projects were significantly less likely to have occurred in block groups with higher tree canopy cover, higher median income, or greater percentages of African American or Hispanic residents, controlling for physical and socioeconomic conditions. In addition, when canopy cover or income was low, plantings were even less likely to have occurred in neighborhoods with high percentages of racial or ethnic minorities. Findings suggest nonprofit

---

<sup>1</sup>San Francisco State University, CA, USA

<sup>2</sup>Indiana University, Bloomington, IN, USA

<sup>3</sup>DePaul University, Chicago, IL, USA

## Corresponding Author:

Shannon Lea Watkins, San Francisco State University, 1600 Holloway Ave., San Francisco, CA 94132, USA.

Email: shannon.l.watkins@gmail.com

plantings might reduce existing income-based inequity in canopy cover, but risk creating or exacerbating race-based inequity and risk leaving low canopy minority neighborhoods with relatively few program benefits.

### **Keywords**

urban tree canopy cover, environmental justice, Atlanta, GA, Detroit, MI, Indianapolis, IN, Philadelphia, PA

## **Introduction**

Greenspace in urban settings provides an array of benefits to those who live near it or are exposed to it, including reduced stress and anxiety (Ward Thompson et al., 2012), improved cognitive functioning (Berman, Jonides, & Kaplan, 2008; Taylor, Kuo, & Sullivan, 2001), and strengthened community (Kweon, Sullivan, & Wiley, 1998; Sullivan, Kuo, & DePooter, 2004). However, poor and minority communities in urban areas often have less access to environmental amenities (Tibbetts, 2002), including greenspace (Comber, Brunsdon, & Green, 2008), public parks (Wolch, Wilson, & Fehrenbach, 2005), and tree canopy cover (Heynen, Perkins, & Roy, 2006; Pedlowski, Da Silva, Adell, & Heynen, 2002). If poor or minority residents have unequal access to urban environmental amenities, then they also have unequal access to the benefits those amenities provide (Jennings & Gaither, 2015), presenting an environmental injustice. To target public policy strategies to promote urban environmental equity, research must build on recent efforts to describe inequity in the distribution of environmental amenities and the historical drivers of that inequity; inquiry into contemporary drivers that might create, exacerbate, or relieve inequity is required.

The urban forest provides many benefits to urban residents; however, like other environmental amenities, there is evidence that urban tree canopy cover is often disproportionately distributed based on socioeconomic characteristics (Danford et al., 2014; Locke & Grove, 2014). Municipal governments and environmental nonprofit organizations in many cities across the United States have undertaken tree-planting programs to increase urban tree canopy cover (McPherson & Young, 2010). Recently, scholars have started to compile evidence that these programs might exacerbate inequity by planting trees in wealthier areas and in areas with higher canopy cover (Donovan & Mills, 2014; Locke & Grove, 2014).

Previous studies of the spatial distribution of tree plantings have not yet isolated nonprofit activities for inquiry, have been largely single-city studies,

and have not directly considered the distribution of tree planting with respect to race or ethnicity. Although municipalities and nonprofit organizations face similar physical constraints when planting trees in cities, nonprofits often have a more targeted mission and more diverse funding sources. Given organizational differences, the distribution of trees planted by nonprofits might be different from that of trees planted by municipalities. In this article, we use a unique data set from four cities in the Midwest and Eastern United States to examine the distribution of nonprofit tree planting. The findings speak to whether tree-planting activities facilitated by urban greening nonprofit organizations might exacerbate or reduce disparity in access to urban tree canopy cover.

## Research Motivation

### *Benefits of Nature and of Trees*

Nature in urban environments provides physical, psychological, and social benefits to nearby residents (see Bowler, Buyung-Ali, Knight, & Pullin, 2010; Haluza, Schönbauer, & Cervinka, 2014; Hartig, Mitchell, De Vries, & Frumkin, 2014; Lee & Maheswaran, 2011, for recent reviews). Observational studies have, for example, demonstrated that greenspace is associated with lower levels of stress (Ward Thompson et al., 2012), moderates the effect of stressful life events on health (van den Berg, Maas, Verheij, & Groenewegen, 2010), provides places for older adults to strengthen neighborhood ties (Kweon et al., 1998), and is related to higher social activity (Sullivan et al., 2004). However, measurement and self-selection issues limit the causal implications of observational studies (Lee & Maheswaran, 2011; Shanahan, Fuller, Bush, Lin, & Gaston, 2015).

Increasingly, research on the benefits of nature uses experimental and natural experimental methods to begin to causally link exposure to nature and public health outcomes. Findings include positive effects on an individual's emotional state (Ulrich, 1981), lower stress and anxiety (Bratman, Daily, Levy, & Gross, 2015; Ulrich, 1979), higher cognitive functioning (Berman et al., 2008), and shorter recovery time after surgery (Ulrich, 1984). Benefits of greenspace have been found across different levels and types of exposure (Berman et al., 2008; Kuo, 2001; Ulrich, 1981). Not all studies have found significant benefits of greenspace on health (Haluza et al., 2014) and there are still gaps in our understanding of how the impact of nature on health is mediated by characteristics of the individuals (e.g., age, gender), of the greenspace (e.g., quality, access; Lee & Maheswaran, 2011) and of the exposure (e.g., duration; Shanahan et al., 2015). Yet, recent reviews of the existing

literature conclude that the evidence demonstrates positive effects of greenspace on individuals and communities (Haluzi et al., 2014; Hartig et al., 2014; Lee & Maheswaran, 2011).

Studies have found urban trees in particular to be associated with health outcomes including lower prevalence of asthma in children (Lovasi, Quinn, Neckerman, Perzanowski, & Rundle, 2008) and with higher ability to focus and to manage major life issues (Kuo, 2001). Trees can also improve local environmental quality for urban residents: they can lower temperatures and mitigate urban heat-island effects (Rosenzweig et al., 2006), improve air quality by capturing particulate matter and reducing atmospheric carbon dioxide (Nowak & Dwyer, 2007), and improve water quality and help manage stormwater (Cappiella, Schueler, & Wright, 2005; Xiao, McPherson, Ustin, Grismer, & Simpson, 2000). Trees also have economic benefits. For example, urban trees can reduce demand for heating and air conditioning by blocking winter winds and summer sun (McPherson & Simpson, 2003), can raise property values (Donovan & Butry, 2010; Tyrväinen & Miettinen, 2000), and can increase visits to and purchases in business districts (Wolf, 2003).

Finally, trees can reduce crime (Bogar & Beyer, 2015) and increase perceptions of safety (Kuo, Bacaicoa, & Sullivan, 1998). For example, a recent quasi-experiment found that the construction of green stormwater infrastructure projects (often containing street trees) was associated with significantly lower occurrence of narcotics possession (Kondo, Low, Henning, & Branas, 2015). Two studies found that tall trees (that did not block views) were associated with fewer instances of crime (Kuo & Sullivan, 2001; Donovan & Prestemon, 2010; although Donovan & Prestemon also found that small trees were associated with higher crime).

It is important to note that there are also costs to urban trees (“ecosystem disservices”; Escobedo, Kroeger, & Wagner, 2011; Lyttimäki, 2014; McPherson & Ferrini, 2010). For example, trees require routine maintenance to prevent property damage and clean leaf litter (Escobedo et al., 2011). Unmaintained, nuisance trees can grow along fences (creating the “fence-line forest”; Heynen et al., 2006). To some urban residents, particularly in many inner-city neighborhoods where residents often rent their homes, new trees in a neighborhood might signal gentrification and displacement rather than neighborhood improvement (Checker, 2011). Increasing property values will, theoretically, raise rents and can displace and exclude low-income residents from areas of the city with improved urban amenities (Wolch, Byrne, & Newell, 2014). Some research has demonstrated that income, ethnicity, and homeownership are not related to preferences about tree canopy (Conway & Bang, 2014), but even if low-income residents value urban trees, they may be distrustful of tree-planting initiatives that might cause displacement.

## *Evidence of Inequity in Distribution of Urban Canopy Cover*

Given the many benefits of trees, evidence of the inequitable distribution of trees in urban environments (Grove, Locke, & O'Neil-Dunne, 2014; Jensen, Gatrell, Boulton, & Harber, 2004; Landry, 2013) raises concerns of environmental injustice. Research has typically documented positive relationships within cities between canopy cover and income (Danford et al., 2014; Heynen et al., 2006; Landry & Chakraborty, 2009; Locke & Grove, 2014; Pham, Apparicio, Séguin, Landry, & Gagnon, 2012; Schwarz et al., 2015). Research has also documented evidence of a negative relationship between canopy cover and the presence of renters (Landry & Chakraborty, 2009). Evidence regarding the distribution of canopy cover with respect to minority residents is mixed (see, for example, the multi-city study by Schwarz et al., 2015). Some studies find a negative relationship between canopy cover and minority populations (Flocks, Escobedo, Wade, Varela, & Wald, 2011; Heynen et al., 2006) and between canopy cover on public rights-of-way and minority populations (Landry & Chakraborty, 2009; Pham et al., 2012). However, others have found no significant relationship (Heynen et al., 2006) or even a positive relationship between minority populations and canopy cover (Danford et al., 2014; Troy, Grove, O'Neil-Dunne, Pickett, & Cadenasso, 2007), trees on private land (Pham et al., 2012), and street trees (Flocks et al., 2011).

## *Mechanisms Driving the Distribution of Urban Trees*

Building on studies of distribution, some studies have examined *historical mechanisms* that drive spatial patterns in urban land use and the distribution of tree canopy cover. Fewer studies have advanced our understanding of how *current activities* will shape the distribution of future tree cover.

Characteristics of past residents and other actors, past biophysical conditions, and previous institutional arrangements shape land cover and may provide explanations for current inequity in canopy distribution (Grove et al., 2014; Mincey, Hutten, et al., 2013). For example, lifestyle choices of previous neighborhood residents were found to best predict tree canopy cover distribution in New York City (Grove et al., 2014). For another example, race-based residential segregation contributed to inequitable distribution of urban trees in Baltimore (Buckley, 2010). Characteristics of the built environment, including land use, intensity of urbanization and settlement age also contribute to urban forest patterns (Nowak, 1994).

There is also evidence that the decisions, resources and policies of local governments, and more recently environmental nonprofit organizations,

significantly influence the urban landscape (Mincey, Schmitt-Harsh, & Thureau, 2013; Mincey & Vogt, 2014; Pincetl, 2003). For example, municipal resources can influence access to greenspace (Joassart-Marcelli, 2010; Wolch et al., 2005). City or state land use policies, like zoning, can also influence patterns of urban tree cover (Hill, Dorfman, & Kramer, 2010; Mincey, Schmitt-Harsh, & Thureau, 2013). Over time, social processes, municipal activities, and the interactions between them have led to the decline of urban canopy cover in many cities across the United States (Nowak & Greenfield, 2012) and to its unequal distribution as described above (Danford et al., 2014; Landry & Chakraborty, 2009).

In light of low and declining canopy cover, municipalities and nonprofit organizations have undertaken urban reforestation efforts through new canopy cover targets and tree-planting goals (Krause, 2011; McPherson & Young, 2010) and tree-planting programs (e.g., through the Alliance for Community Trees' National NeighborWoods program; <http://www.actrees.org>; <http://www.neighborwoodsmoth.org>). Although these programs will likely increase overall future urban canopy cover, their effect on canopy cover distribution is unclear. For example, a program that responds to resident requests for trees (an "opt-in" program), might actually result in more tree plantings (and subsequently higher future canopy cover) in wealthy neighborhoods where residents have access to information about and resources to take advantage of the program.

### *Evidence of Uneven Distribution of Tree-Planting Activities*

Several recent studies have investigated whether the locations of contemporary tree-planting activities are related to the socioeconomic characteristics of urban residents and the level of existing tree canopy cover. These studies considered planting activities undertaken by municipalities alone or with support from a local nonprofit organization, including free or reduced-cost tree programs (Donovan & Mills, 2014; Perkins, Heynen, & Wilson, 2004) and telephone hotlines (3-1-1 lines) where residents can request trees (Locke & Grove, 2014). These studies found that planting activity is positively related to existing canopy cover in Baltimore and Washington, D.C. (Locke & Grove, 2014) and the presence of existing street trees in front of the house in Portland (Donovan & Mills, 2014). They also found a positive relationship between planting activities and socioeconomic characteristics, including income in Baltimore and Washington, D.C. (Locke & Grove, 2014), housing age and education in Portland (Donovan & Mills, 2014), and homeownership in Milwaukee (Perkins et al., 2004). Generally, the authors conclude that plantings might exacerbate inequity in canopy cover by planting in leafier and more

well-to-do neighborhoods. To our knowledge, none of these studies test specifically the relationship between planting location and race and ethnicity.

A few other studies tackle this question more indirectly and found similar results. For example, authors have found a positive relationship between canopy cover in public rights-of-way (assumed to be planted by municipalities) and income, homeownership, and household age in Tampa, Florida (Landry & Chakraborty 2009). Conway and Bang (2014) found related evidence in Canada that individuals who plant and have more trees on their private property demonstrate higher support for urban tree policies, suggesting that these same individuals might more readily participate in or advocate for planting activities.

### *Factors That Might Drive Planting Locations*

In many cities, private and nonprofit entities also plant trees (Duinker, Steenberg, Ordóñez, Cushing, & Perfitt, 2014; Young & McPherson, 2013), in some cases taking sole responsibility for planting trees in public rights-of-way (e.g., Keep Indianapolis Beautiful in Indianapolis, Indiana [kibi.org] and The Greening of Detroit in Detroit, Michigan [greeningofdetroit.com]). Nonprofits and municipalities share some of the same objectives and constraints, and so the distribution of their plantings might be quite similar. However, several organizational differences suggest that the distribution of nonprofit plantings might differ from that of municipal plantings.

*Physical suitability.* Municipalities and nonprofits are constrained by characteristics of the physical urban environment, like urban density and the location of city green spaces (Bowen, 2002). Often, municipalities are further limited to planting (or providing funds to plant) on public land, such as in the public rights-of-way or in public parks (see, for example, Community Urban Forestry grants from the Indiana Department of Natural Resources; [http://www.in.gov/dnr/forestry/files/fo-grant\\_guidelines.pdf](http://www.in.gov/dnr/forestry/files/fo-grant_guidelines.pdf)). Nonprofit organizations might have more flexibility in planting location, particularly when using non-governmental funds. With potentially fewer constraints on planting location, nonprofit projects might yield higher distributional equity.

*Funding.* Nonprofits often serve as tree-planting contractors for municipal governments. To the extent that nonprofit funding comes from municipalities, the distribution of tree plantings might reflect that of municipal plantings (e.g., because they are constrained to plant on public land; see preceding paragraph). But nonprofits also seek grants and receive donations from other sources (private individual donors, philanthropic foundations, local

businesses, etc.), which might enable nonprofits to pursue a different mission or agenda than that of the municipal agency.

*Neighborhood interest and capacity.* Many municipal and nonprofit programs engage residents in tree-planting activities, including making requests for trees, choosing tree locations and species, and planting and caring for trees. In some nonprofit programs, neighbors and the nonprofit collectively plan and implement a project to plant many trees at once in a neighborhood. The interest and collective capacity of a neighborhood is likely related to whether a neighborhood participates in a planting project. For example, Greening of Detroit describes their community plantings: “If a neighborhood group in Detroit asks us to plant trees, we do everything we can to plant there” ([www.greeningofdetroit.com](http://www.greeningofdetroit.com)). Nonprofits might require some neighborhood capacity for tree maintenance before they agree to plant trees with the neighborhood (e.g., a management plan or a certain number of volunteers). If interest or collective capacity is related to income, race, and/or ethnicity, these characteristics might be related to nonprofit planting project locations.

*Mission.* The missions of municipalities and nonprofits likely differ. For instance, municipal governments provide more public goods and services (e.g., infrastructure, public safety, fire prevention) than more narrowly focused urban greening nonprofits. In addition to increasing canopy cover, many urban greening nonprofits also have a social mission. For example, Urban Releaf, in Oakland California addresses “the needs of communities that have little to no greenery or tree canopy” and focuses on “under-served neighborhoods that suffer from disproportionate environmental quality of life and economic depravity” ([www.urbanreleaf.org](http://www.urbanreleaf.org)). Greening of Detroit’s mission is to inspire “sustainable growth of a healthy urban community through trees, green spaces, food, education, training and job opportunities” ([www.greeningofdetroit.com](http://www.greeningofdetroit.com)). With narrower and potentially more social missions or goals, nonprofits might be able to better address inequity.

### *Research Objective and Contributions*

While there have been numerous efforts to describe the distribution of the urban forest, fewer efforts have considered the distributional impacts of ongoing tree-planting efforts, particularly those of nonprofits and particularly with regard to race and ethnicity. In this article, we test whether the location of nonprofit tree-planting projects are related to three primary neighborhood characteristics: (a) the extent to which the neighborhood has a physical need for trees (operationalized as canopy cover), (b) whether the neighborhood has



sufficient financial resources to plant trees without nonprofit/government assistance (operationalized as household income), and (c) the racial and ethnic composition of neighborhood residents (hereon referred to as race and ethnicity). If nonprofit programs exacerbate environmental inequities, we expect to find nonprofit tree-planting projects more likely to occur in neighborhoods with low physical need (high existing tree canopy cover) and high financial resources, and less likely to occur in neighborhoods with a larger percent of racial and ethnic minority residents. Finally, recognizing potential interactive effects between race, ethnicity, income, and canopy cover, we test the relationships again including two-way interaction terms between the primary variables of interest.

## Study Sites

We leveraged data on nonprofit tree-planting activities from four urban greening nonprofit organizations: The Greening of Detroit (Detroit, MI), Keep Indianapolis Beautiful, Inc. (Indianapolis, IN), Pennsylvania Horticultural Society (Philadelphia, PA), and Trees Atlanta (Atlanta, GA). Nonprofit partners were selected because each organization works with local community groups to plant trees in urban neighborhoods in a single metropolitan area in the Midwest or Eastern United States. The nonprofit must also have been a member of the Alliance for Community Trees, a national advocacy and grant-disbursing nonprofit. Each nonprofit must have recorded the locations of individual trees planted between 2009 and 2011.

In each program, either the nonprofit or a local community group (i.e., a neighborhood or homeowners association; business association; church, etc.) initiates a process to plant trees in the neighborhood. This process may include any or all of the following: completing a form or application, designating a specific location in the neighborhood where trees are desired, soliciting volunteers from the neighborhood to help plant the trees, receiving in-person training on proper methods of tree planting and care, and watering the trees for a year or more after planting. In return, the community group receives free or reduced-cost trees to plant.

We used census block groups as the unit of analysis. Block groups, an administrative unit used by the U.S. Census Bureau, contain between 600 and 3,000 people and are the smallest geographic unit for which the U.S. census bureau publishes both census and sample data. Sample data are collected only from a sample of households and contain more socioeconomic information than the census data. Block groups reasonably capture the population that might benefit from the planted trees. Using smaller, parcel-level units would ignore the spillover benefits of planted trees while using larger neighborhood

boundaries would capture areas that did not receive the localized benefits of planted trees. Using block groups allowed inclusion of socioeconomic data. The total number of block groups across all four cities in this study was 3,798 (3,771 in full models; some block groups were dropped because of incomplete census data).

## Methods

We conducted our analysis in four steps. First, we used bivariate regression to estimate the relationship between canopy cover (as a dependent variable) and the other two neighborhood characteristics of interest. We then investigated the relationship between tree-planting location and all three neighborhood characteristics in three steps. In Step 2, we visualized the data by generating maps of tree-planting locations and of each neighborhood characteristic—canopy cover, income, and race and ethnicity. In Step 3, we tested the relationship between planting location and the primary neighborhood characteristics in a parsimonious model and then again controlling for other physical and socioeconomic characteristics of the neighborhood. We used cross-sectional data of nonprofit tree-planting locations to estimate linear probability and probit models with city fixed effects. Finally, in Step 4, we introduced two-way interaction terms between canopy cover and income, canopy cover and race and ethnicity, and income and race and ethnicity to the model.

## Data

*Planted neighborhoods.* The dependent variable is a binary indicator of whether a census block group had any trees planted between 2009 and 2011 as part of a nonprofit project. Locations of planted trees were provided by the nonprofit partners and each planted tree was mapped with a Geographic Information System (GIS; ArcGIS Desktop, 10.2). Census block groups that had at least one tree planted between 2009 and 2011 were coded 1 ( $n = 1,160$ ; “planted block groups”) and block groups that did not have a planted tree between 2009 and 2011 were coded 0 ( $n = 2,638$ ; “nonplanted block groups”).

*Variables of interest.* We indicated a neighborhood’s physical need for trees by the percent of land area in the block group that is covered by tree canopy. Measures of block group level tree canopy cover were generated using remote sensing techniques and 2013 National Agricultural Imagery Program (NAIP) imagery—high resolution aerial imagery from the U.S. Department of Agriculture (see online appendix for a complete description of remote sensing

methods). These data were collected a few years after the plantings in our study occurred (2009-2011), but we do not expect the small planted trees to make a significant difference in canopy cover estimates at the block group level. If all trees planted between 2009 and 2011 survived (a generous assumption), we estimate they would comprise on average 0.13% of total block group canopy cover in block groups where they were planted. (These estimates were generated using tree inventory data gathered in 2014 and iTree Streets. See Widney, Fischer, & Vogt, 2015, for details on data collection.)

To capture financial resources, we included a measure of the median household income (in thousands of dollars) of the census tract that contains the block group from the 2010 American Community Survey (ACS). Neighborhood racial and ethnic composition were measured by the percent of individuals who are African American and the percent of individuals who are Hispanic in a block group, respectively, from the 2010 U.S. Census.

There are two differences between the income variable (from the ACS) and the race and ethnicity variables (from the U.S. Census) that yield higher measurement error in the income variable than in the race and ethnicity variables: (a) Race and ethnicity are measured at the block group level and income is measured at the tract level and (b) race and ethnicity come from a complete census of residents, whereas income is estimated from a subsample of the population. These two differences mean that the race and ethnicity estimates are more precise than the income estimates.

*Control variables.* In addition to the primary variables described above, we included a suite of control covariates in the regression analysis. Scholars have noted the importance of controlling for other covariates in environmental justice inquiries (e.g., see Ringquist, 2005), including other socioeconomic characteristics and physical constraints (Bowen, 2002). This inclusion allowed us to estimate the unique relationship of planting and, for example, income, controlling for other factors that are both related to tree planting and to our independent variables of interest.

*Physical suitability.* Neighborhoods with high physical suitability for planting might be more likely to be the location of a planting project. Including indicators of tree-planting potential in a block group helped limit our study area to locations that might actually be chosen for tree planting (Bowen, 2002). To capture physical suitability, we included (a) a measure of potential canopy cover—the percent of a block group that is herbaceous cover or soil—generated using remote sensing techniques (described in online appendix); (b) total block group area in hundreds of hectares, measured in a GIS; (c) population density in the block group from the 2010 U.S. Census; and

(d) the percent of commuters who walk to work in the tract from the 2010 ACS. We include block group area as a proxy for available plantable land and include percent pedestrian commuters as a proxy for the presence of sidewalks in a neighborhood, which often provide potential planting areas for trees (in tree pits or adjacent planting strips).

*Neighborhood characteristics.* It might be the case that certain types of neighborhoods are more likely to apply for tree-planting projects (because they have free time or knowledge about the program, for example) or the case that the nonprofit recruits or plants in certain locations related to neighborhood characteristics. To capture neighborhood characteristics, we included the percent of housing units that are renter occupied, the percent of households that have a female head of household, and the percent of families with children (block group data from the 2010 U.S. Census). Some demographic data are not available at the block group level and so we use tract-level data to capture the percent of individuals older than 25 years who have earned at least a bachelor's degree, the percent of individuals who are unemployed, and the percent of individuals who have moved into their house since 2005 (from ACS).

### *Model Specification*

To test the relationship between planting location and neighborhood characteristics, we estimated a series of models that predict whether a block group is a planted block group. First, we estimated a set of parsimonious models that contain only our four variables of interest: tree canopy cover, median household income, and the percent of residents who are African American and who are Hispanic. We then estimated a set of full models that include our primary variables of interest and a suite of control variables. For each of these sets of independent variables, we estimated a linear probability model (LPM) that provides easily interpretable coefficients and we estimated a probit model. Because city-level characteristics might account for variation in the outcome, we also estimated both the LPM and probit models with fixed effects to control for this city-level variation. The intraclass correlation coefficient is .15, suggesting that between-city information does not account for substantial variation in the outcome. However, it seems unlikely that city-level characteristics are unrelated to our outcome and independent variables. The result of a Hausman test between the LPM models rejected the null hypothesis that there is no difference between random effects and fixed effects models, and so we use the more consistent fixed effects model. Our preferred model is thus a probit model with fixed effects.

To test whether the effect of each primary independent variable changes over the values of the others, we specified a model that included the following two-way interaction terms: canopy and income, canopy and percent African American, canopy and percent Hispanic, income and percent African American; and income and percent Hispanic.

### **Robustness Checks**

We conducted several robustness checks. We obtained records from each nonprofit for a number of years outside the 2009-2011 window where available (Greening of Detroit, 2012-2013; Keep Indianapolis Beautiful, 2006-2008, 2012-2013; Pennsylvania Horticultural Society, 2008; Trees Atlanta, 1993-2008). Record keeping improved over time, so the earliest years of data might be incomplete. We generated a second dependent variable in which any block group that contained a planted tree in any year of available data was coded as 1 ( $n = 1,439$ ) and re-ran the models.

Previous work on the equity of the distribution of tree plantings did not explicitly include race or ethnicity. To check the robustness of our results with respect to canopy cover and income, we estimated the models without percent African American and percent Hispanic. Given high correlation between education and income, which could inflate standard errors and create unstable coefficients, we also ran a set of models without controlling for education. To get a sense of inter-city variation in results, we ran a parsimonious probit model for each city. Finally, we tested for spatial autocorrelation within each city by generating a Moran's  $I$  in ArcGIS. If observations (in this case, tree-planting project locations) are not randomly distributed across a city, there is autocorrelation in the error term and our assumption of independent observations is violated.

### **Results**

Table 1 presents descriptive statistics for each variable. Overall, 31% of block groups were planted. Table 2 presents descriptive statistics of the primary variables of interest separated for planted and nonplanted block groups. Of note, average tree canopy cover in nonplanted block groups is approximately 10 percentage points higher than in planted block groups and the average percent of African American residents is approximately 15 percentage points higher in nonplanted block groups. Table 3 presents the number of observations, the number and proportion of planted block groups, and the independent variables of interest by city. Table 3 reveals there are many more block groups in Philadelphia than in the other three cities and planting incidence varies substantively across cities.

**Table 1.** Descriptive Statistics for Variables Included in Pooled Models.

Variable	Observations	M	Minimum	Maximum	Median	SD
Trees (09-11) <sup>a</sup> (= 1 if project 2009-2011)	3,798	0.31	0	1	0	0.46
Trees <sup>a</sup> (= 1 if any project)	3,798	0.38	0	1	0	0.49
% tree canopy cover	3,795	33.48	0	89.30	30.5	20.31
Median hh income (US\$1,000) <sup>b</sup>	3,780	41.95	9.29	207.50	35.646	24.22
% African American	3,789	53.23	0	100	56.7	37.97
% Hispanic	3,789	9.07	0	96.20	3.4	15.44
Potential canopy cover	3,795	18.19	0.50	76.70	16.3	11.09
Block group area (100s ha)	3,798	1.02	0.02	102.23	0.37265	2.95
% walking commuters <sup>b</sup>	3,781	4.37	0	73.7	2	7.80
Population density	3,798	43.05	0	622.48	25.24	45.55
% renters	3,787	44.90	0	100	43.4	22.78
% female head of hh	3,787	52.12	0	100	53.2	11.42
% families with kids	3,781	52.90	0	100	53.5	11.74
% bachelor's or higher <sup>b</sup>	3,784	24.40	0	92.6	16.2	21.49
% unemployment	3,782	15.44	0	100	14.1	9.74
% moved within 5 years <sup>b</sup>	3,782	37.75	0	100	36	13.93

Note. hh = household.

<sup>a</sup>Denotes dependent variables.

<sup>b</sup>Identifies variables at the census tract level.

### *Relationship Between Canopy Cover and Income, Race, and Ethnicity*

To estimate whether there is existing inequity in the study cities, we conducted bivariate regressions in which canopy cover is the dependent variable and income, race, and ethnicity are independent variables. Table 4 presents the results, which are largely consistent with previous research in other cities. Across all four cities, canopy cover is positively and significantly related to income. Results based on ethnicity are also consistent across cities—canopy cover is negatively and significantly related to percent Hispanic. Results based on race are less consistent. All coefficients are positive (suggesting

**Table 2.** Descriptive Statistics for Primary Explanatory Variables of Interest, by Whether a Neighborhood Had Been the Location of a Planting Between 2009 and 2011 (Trees = 1) or Had Never Been the Location of a Planting (Trees = 0).

Variable	Trees	Observations	M	Minimum	Maximum	Median	SD
% tree canopy cover	0 1	2,635 1,160	36.77 26.00	0 1.80	89.30 81.00	34.10 21.50	20.52 17.69
Median hh income (US\$1,000) <sup>a</sup>	0 1	2,621 1,159	42.01 41.82	9.29 10.75	207.50 135.46	35.37 37.14	25.58 20.85
% African American	0 1	2,629 1,160	57.88 42.67	0 0	100 99.10	73.50 30.20	37.75 36.35
% Hispanic	0 1	2,629 1,160	8.61 10.11	0 0	96.20 91.20	3.10 4.10	14.77 16.83

Note. hh = household.

<sup>a</sup>Identifies variables at the census tract level.

**Table 3.** Descriptive Statistics of Key Variables by City.

City	Block groups		Trees (09-11)		Canopy		Med hh income (1,000s) <sup>a</sup>		% African American		% Hispanic	
	n	% of total	n	% of city	M	SD	M	SD	M	SD	M	SD
Atlanta	934	24.59	180	19.27	58.45	15.01	59.52	33.32	48.45	37.87	8.20	13.73
Detroit	896	23.59	188	20.98	34.07	10.67	29.78	12.12	84.06	24.27	5.70	16.28
Indianapolis	632	16.64	160	25.32	30.01	13.46	44.26	19.86	28.88	28.00	9.19	9.24
Philadelphia	1,336	35.18	632	47.31	17.32	12.29	36.71	16.18	47.42	36.95	11.88	17.68
All cities	3,798	100.0	1,160	30.54	33.48	20.31	41.95	24.22	53.23	37.97	9.07	15.44

<sup>a</sup>Identifies variables at the census tract level.

higher canopy cover as the percent of African American residents increases), but the relationship is only significant in Atlanta and Detroit.

### Relationship Between Tree Planting and Canopy, Income, Race, and Ethnicity

To examine the data visually, the dependent variable and primary independent variables were plotted in a GIS. Figure A1 in the online appendix displays five maps for each city: Map A displays block groups that were planted between 2009 and 2011 and Maps B through E display the four primary variables of interest by quintile. By eye, the maps suggest some

**Table 4.** City and Pooled Models: Canopy and Income, Race, and Ethnicity.

City	Independent variable		
	Median hh income (US\$1,000) <sup>a</sup>	% African American	% Hispanic
Atlanta ( <i>n</i> = 927) <sup>b</sup>	0.104** (0.014)	0.040** (0.013)	-0.275** (0.034)
Detroit ( <i>n</i> = 894) <sup>b</sup>	0.184** (0.029)	0.134** (0.014)	-0.193** (0.021)
Indianapolis ( <i>n</i> = 632)	0.263** (0.025)	0.009 (0.019)	-0.452** (0.055)
Philadelphia ( <i>n</i> = 1,333) <sup>b</sup>	0.215** (0.020)	0.011 (0.009)	-0.158** (0.019)
All cities ( <i>n</i> = 3,786) <sup>b</sup>	0.353** (0.012)	0.043** (0.009)	-0.295** (0.021)

Note. Each coefficient represents a different bivariate regression between canopy cover and the noted independent variable. Standard errors in parentheses. hh = household.

<sup>a</sup>Identifies variables at the census tract level.

<sup>b</sup>Sample size for % African American and % Hispanic. Sample size smaller for income models because of missing census data: Detroit: 891, Philadelphia: 1,327, all cities: 3,777.

\* $p < .05$ . \*\* $p < .01$ .

relationships between planting and our independent variables of interest. For example, plantings in Atlanta and Indianapolis are clustered in the urban core, where canopy cover and median income also appear lower. In Philadelphia, plantings seem to cluster in areas of low canopy cover along the southeast and northeast portions of the city and in areas of higher canopy cover in the northwest. Plantings in Atlanta and Philadelphia also seem to cluster in areas with low African American populations. Relationships are unclear in Detroit, where neighborhoods seem to be less clustered by sociodemographic characteristics.

### Regression Analysis

Basic *t* tests ( $\alpha = .05$ ) indicate that tree canopy cover is lower in planted block groups than in nonplanted block groups ( $t = -15.51$ ;  $p = .000$ ); there is no significant difference in median household income between groups ( $t = -.23$ ;  $p = .822$ ), a significantly lower percent of African American residents in planted neighborhoods ( $t = -11.56$ ;  $p = .000$ ), and a significantly higher percent of Hispanic residents in planted neighborhoods ( $t = 2.75$ ;  $p = .006$ ).

Table 5 presents the results of our preferred models (see additional model results in online appendix: Tables A1 and A2 for LPM, LPM with fixed effects, probit model, and probit model with fixed effects). The LPM coefficients can be interpreted as an increase in the probability that a block group had a tree-planting project given a one-unit increase in the explanatory variable. The coefficients from the probit models are more difficult to interpret



**Table 5.** Regression Results for Preferred Models: Planting Between 2009 and 2011 in All Cities.

	Model 1 Probit, FE	Model 2 Probit, FE with controls	Model 3 Probit with interactions
% tree canopy cover	-0.01315** (0.00188)	-0.01548** (0.00209)	-0.02173** (0.00574)
Median hh income (US\$1,000) <sup>a</sup>	-0.00163 (0.00137)	-0.00729** (0.00239)	0.00538 (0.00448)
% African American	-0.00836** (0.00088)	-0.00637** (0.00124)	-0.01262** (0.00223)
% Hispanic	-0.00849** (0.00167)	-0.00424* (0.00195)	0.01429** (0.00435)
% potential canopy	—	-0.00724* (0.00319)	0.00003 (0.00004)
Block group area	—	-0.05727** (0.01979)	-0.00085** (0.00017)
% walking commuters <sup>a</sup>	—	0.00009 (0.00379)	-0.01217** (0.00278)
Population density	—	-0.00219** (0.00084)	-0.07871** (0.02012)
% renters	—	-0.00079 (0.00152)	0.00066 (0.00384)
% female head of hh	—	0.00056 (0.00373)	-0.00089 (0.00080)
% families with kids	—	-0.00043 (0.00263)	-0.00024 (0.00156)
% bachelor's or higher <sup>a</sup>	—	0.01547** (0.00260)	0.00056 (0.00374)
% unemployment <sup>a</sup>	—	0.00687 (0.00370)	0.00447 (0.00273)
% moved within 5 years <sup>a</sup>	—	-0.00109 (0.00270)	0.01723** (0.00276)
Median hh Income × % African American	—	—	0.00585 (0.00359)
Median hh Income × % Hispanic	—	—	-0.00547* (0.00256)
% Canopy × % African American	—	—	0.00016** (0.00005)
% Canopy × % Hispanic	—	—	0.00011 (0.00014)

(continued)

**Table 5. (continued)**

	Model 1 Probit, FE	Model 2 Probit, FE with controls	Model 3 Probit with interactions
% Canopy × Median hh Income	—	—	-0.00018* (0.00007)
Constant	0.43221** (0.14477)	0.29590 (0.28686)	0.42345 (0.31835)
Number of observations	3,774	3,771	3,771
Likelihood ratio	-2,099.750	-2,054.293	-2,032.406
Pseudo R <sup>2</sup>	.098	.117	.126
AIC	4,215.501	4,144.586	4,104.812
BIC	4,265.388	4,256.818	4,229.514

Note. Coefficients shown with standard errors in parentheses. "FE" signifies a model run using fixed effects (coefficients for city fixed effects not shown). AIC = Akaike information criterion; BIC = Bayesian information criterion; hh = household.

<sup>a</sup>Identifies variables at the census tract level.

\* $p < .05$ . \*\* $p < .01$ .

because the increase in probability of planting from a one-unit increase in an explanatory variable depends on the values of the other explanatory variables. Although the coefficient estimates are not comparable between the LPM and the probit model, the direction and significance can be compared. Because of the complexity in interpretation and because the answer to the question posed here is more concerned with hypothesis testing than calculating predicted probabilities, we will focus interpretation on the direction and significance of the parameter estimates.

In Table 5, Model 1 (the parsimonious model), three of the four primary variables of interest are both negative and significant (these results are consistent across all four models, see Table A1 in online appendix). In other words, in this sample, the probability of tree planting decreases as canopy cover increases, decreases as the percent of African American residents increases, and decreases as the percent of Hispanic residents increases. In the parsimonious models, there is no significant relationship between median household income and planting.

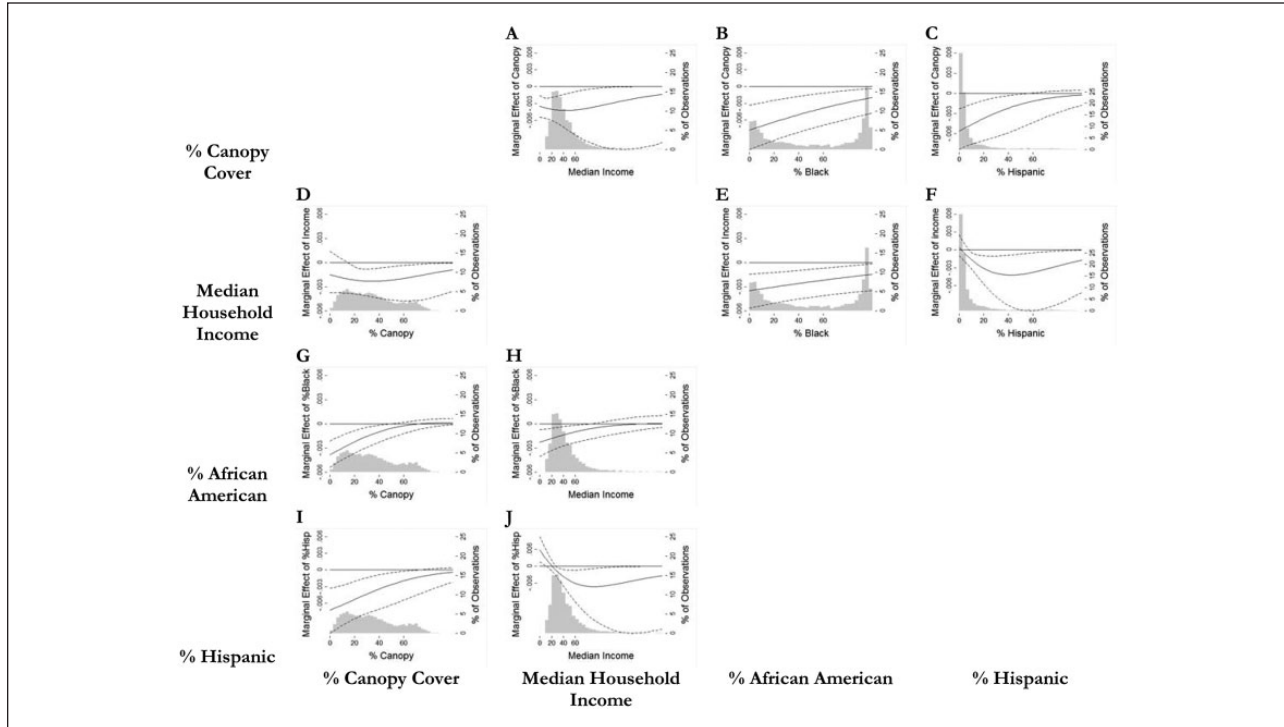
The results after including control variables (Table 5, Model 2) are largely consistent with the more parsimonious models (Table 5, Model 1), but income is now also negative and significant (these results are also consistent in all four models; see Table A2 in online appendix). Several control variables are

also of note. The percent of potential canopy cover in a block group is significant, indicating that planting is less likely to occur as the percent of herbaceous cover and soil increases. Also, the percent of individuals with at least a bachelor's degree is positively and significantly related to tree planting, indicating that more educated neighborhoods are more likely to have a planting, holding other neighborhood features constant. Larger block groups are less likely to have a planting in the probit models, and in the models with fixed effects, population density is negatively and significantly related to planting location.

The probit model with controls and city fixed effects correctly predicted planted status for 74.7% of block groups. It under-predicted tree planting (correctly predicted 32.1% of block groups where planting occurred and correctly predicted 93.6% of block groups where tree planting did not occur). Predictions were significantly better in Atlanta and Detroit and significantly worse in Philadelphia. Another goodness of fit measure, the Henriksson–Merton measure, takes the sum of the proportion correctly predicted for tree planting and for non-tree-planting block groups (Mcintosh & Dorfman, 1992). If that sum is over 1, the model has positive explanatory power. If it is equal to 2, the model has perfectly predicted the dependent variable. The Henriksson–Merton measure for the primary probit model is 1.26, indicating positive explanatory power.

### *Interaction Effects*

Table 5, Model 3 presents the regression results for a probit model that includes two-way interaction terms. Figure 1 graphs the marginal effects of each variable of interest (i.e., the relationship between planting and the variable of interest), conditioned on the other independent variables of interest. The graphs plot the change in the probability that a block group is the location of a tree-planting project due to a one-unit change in the variable  $z$  (the marginal effect of  $z$ ), over changing values of  $x$ . In each graph, the solid line represents the change in probability that a block group is the location of a tree-planting project due to a one-unit change in the variable  $z$ , at all relevant values of  $x$ . The dotted lines represent the 95% confidence interval. For values of  $x$  where the confidence interval falls completely above or below the flat line at 0, the marginal effect of  $z$  is significant at those values of  $x$ . The slope of the line indicates the change in the marginal effect of  $z$  over values of  $x$ . A slope of zero would indicate that the marginal effect of  $z$  is not conditional on (does not change over) values of  $x$ . A histogram of  $x$  is displayed behind each graph to reflect the relevant range of observations.



**Figure 1.** Marginal effects of the independent variables of interest, conditional on the other independent variables of interest. *Note.* Each graph reflects a two-way interaction between the variable on the x-axis (variable x) and the variable on the y-axis (variable z). In each graph, the middle line represents the change in probability that a block group is the location of a tree-planting project due to a one-unit change in the variable z. The outside lines plot the 95% confidence interval. The marginal effect of z is significant at a value of x only if the confidence interval does not contain zero at that value of x. A histogram of x is displayed behind each graph to reflect the relevant range of observations.

The most notable result from these graphs is that the relationships of race and ethnicity and tree-planting location change over values of canopy cover (and the inverse—the effect of canopy cover depends on values of race and ethnicity). Panels G and I of Figure 1 reveal that the negative marginal effect of percent African American and percent Hispanic decreases as canopy cover increases. Both are only significant over a portion of the range of canopy cover values. The marginal effect of percent African American is no longer significant above values of canopy cover over about 50% (Figure 1, Panel G). The marginal effect of Hispanic is no longer significant above canopy cover values over about 70% (about 5.9% of block groups; Figure 1, Panel I).

In other words, race and ethnicity have a stronger relationship with planting location in low canopy areas and they have no significant relationship with planting location in high canopy areas. In Panels B and E of Figure 1, the marginal effects of canopy cover and income become less negative (smaller in magnitude) as the percent of African American residents in a block group increases. In low-income neighborhoods, race plays a more important role in predicting tree planting than it does in high-income neighborhoods. Of note, the relationship between income and Hispanic is reverse—The marginal effect of income is not significant in neighborhoods with low Hispanic populations, and as the Hispanic population increases, the effect of income becomes increasingly negative.

### **Robustness Checks**

The results are fairly robust across model specifications—there are no major changes in significance or sign in the independent variables of interest across all four models (Tables A1 and A2). Model results using the second dependent variable with all available planting data (see results in online appendix, Table A3) are not substantially different in significance or direction from the original models. Only the coefficient on Hispanic in the probit model with fixed effects is no longer significant. Magnitude changes are small—income is slightly more important and canopy cover is slightly less. All four models were also run with the original dependent variable (2009-2011) but without percent African American and percent Hispanic (see results in online appendix, Table A4). The results are substantially the same with and without race and ethnicity—coefficients on canopy cover and median household income are all negative and significant. There are small changes in magnitude: Coefficients on canopy cover are slightly more negative and coefficients on income are slightly less negative in the models that exclude race and ethnicity. As another check, we removed education from the models (see results in online appendix, Table A5). Canopy cover, race, and ethnicity do not change

**Table 6.** Spatial Autocorrelation Tests by City.

	Moran's <i>I</i>	<i>p</i> value	<i>z</i> score
Atlanta	0.605	.000	98.060
Detroit	0.150229	.000	14.124
Indianapolis	0.329506	.000	27.97235
Philadelphia	0.263329	.000	49.514

Note. Moran's *I* values range from  $-1$  (perfect dispersion) to positive  $1$  (perfect correlation/clustering). Values near  $0$  indicate random distribution of tree-planting projects. The *p* value and *z* score indicate whether the spatial pattern is significant. Generated by Paul McCord.

sign or significance, but income is no longer significant and the sign is positive. The absolute magnitude of the coefficient on income is small.

We also ran a parsimonious probit model for each city to get a sense of inter-city variation in results (see results in online appendix, Table A6). Canopy cover is negative in all four cities, and significantly so in all but Philadelphia. Household income (which was not significant in the parsimonious pooled model) is negative and significant in Atlanta and positive and significant in Detroit. Race and/or ethnicity-based inequity is present in three cities. Planting is less likely as the percent of African American residents increases in Atlanta and Philadelphia (and is not significant in Detroit and Indianapolis). Hispanic is significantly negative in three of four cities, and is positive and significant in Detroit.

We generated a Moran's *I* in each city to determine whether there was spatial autocorrelation in the dependent variable. Table 6 presents Moran's *I*, *p* values, and *z* scores. Tests reveal high clustering in Atlanta, significant but weak clustering in Indianapolis and Philadelphia, and a near random spatial pattern in Detroit. Given that spatial autocorrelation is only high in one city, and it is difficult to account for spatial autocorrelation in a multi-city model, we do not run additional regression analysis to account for spatial autocorrelation. Future city-specific models should address the moderate clustering we find.

## Discussion and Conclusion

The analysis in this article evaluates the distributional implications of recent nonprofit urban tree-planting programs with regard to existing canopy cover, income, race and ethnicity. Whereas previous studies found that municipal (or mixed) tree-planting activities were more likely to occur in areas with higher income and higher tree canopy cover, this article finds the opposite in

nonprofit plantings—The probability that a neighborhood was the location of a tree-planting project *decreased* as neighborhood canopy cover and household income *increased*. The findings related to canopy cover are robust across all model specifications. The findings related to income are not significant in the parsimonious models or when education is excluded from the model but are negative and significant when education is controlled for in the full models. The probability of tree planting is also higher in more highly educated neighborhoods. These results suggest that the distribution of nonprofit plantings is related to both income (lower income neighborhoods might have planting projects holding other characteristics constant) and education (more highly educated neighborhoods might have planting projects holding other characteristics constant).

There are several features of nonprofit programs (at least those in this study) that often differ from municipal plantings that might result in more just outcomes. In this article, we cannot test whether and how these mechanisms drive the spatial distribution of tree planting, but discussing them here highlights future avenues for research. First, the tree plantings by the nonprofits in this study were coordinated with neighborhood or community organizations and required collective activity to implement, unlike many municipal programs. In their study in four neighborhoods in Canada, Conway and Bang (2014) find that low support for municipal urban forestry policy appeared to come from individuals' inability to care for trees, concern about risks from large trees, and few resources to plant and maintain trees. Through its recruitment and application process, the nonprofit might be able to encourage and assist particular neighborhoods that otherwise might have limited ability to plant and care for trees. If nonprofits work more directly with community members, they might be able to reduce the risks and costs to, and concerns of, city residents. Collective plantings might also result in trees planted near residents who otherwise would not have capacity or interest in planting or maintaining trees on their own. Municipal programs that simply respond to resident requests might not reduce barriers to participation and miss neighborhoods in need.

Nonprofits have an array of funding sources that might allow them to overcome physical constraints that municipalities face. For instance, while municipalities are often constrained to plant on public land, nonprofits can use donor money to plant trees on private land—most often in front yards along the street. This might reduce the physical barriers to planting in neighborhoods that are densely populated and have high impervious surface cover, and that may lack planting spaces in the public rights-of-way. Having other sources of funding might also give nonprofits the flexibility to let the physical and financial needs of neighborhoods drive their planting decisions.

Finally, nonprofit organizations might simply have different missions and goals than municipalities. For example, one partner nonprofit in this study, Keep Indianapolis Beautiful, Inc., identified both deficit in tree canopy cover and low income as characteristics of target neighborhoods (Wilson & Lindsey, 2009) and seeks to plant in these neighborhoods.

It could also be the case that methodological differences across studies contribute to differences between our results and the results of previous work (e.g., the scale of the unit of analysis, inclusion of race and ethnicity). However, previous studies that measure effects at the household or parcel level (e.g., Donovan & Mills, 2014) and at larger scales (see Locke & Grove, 2014) both find different results than those in this study. Differences in results are also not driven by the inclusion of race and ethnicity. Regression results for models that exclude race and ethnicity reveal negative and significant relationships between planting location and both canopy cover and income.

This article also considered the distribution of tree planting with respect to race and ethnicity and finds, across all four model specifications, planting was less likely to occur as neighborhood minority composition increased. The results also reveal an interaction effect between race and ethnicity and canopy cover and income. For example, the relationships between planting location and both canopy cover and income become less negative as the percent of African American residents increases, which suggests that physical (canopy cover) and financial (income) needs are less important predictors of planting location in predominantly African American neighborhoods than they are in predominantly White neighborhoods. In other words, among the neighborhoods in the *most* physical and financial need of trees, neighborhoods with larger African American populations might actually be even *more* unlikely to be the location of a tree planting than neighborhoods with larger White populations. The results also reveal that the marginal effect of race decreases as median income increases—in other words, differences by race and ethnicity in planting primarily occur in poor neighborhoods.

We should note here that while the relationships identified in this article are statistically significant, they are substantively small. This is not surprising. Coefficients measure the change in probability over a one-unit change in the independent variable (a percentage point for canopy cover, race, and ethnicity, and US\$1,000 for income). Given the often spatially segregated nature of cities (see the histogram in Panel B, Figure 1), it might be more appropriate to think about the change in probability over a 50-unit (i.e., 50 percentage-point) change in race—moving from a predominantly White neighborhood to a predominantly Black neighborhood. Coefficients also capture the effects of one program (tree planting) over a small period of time (between 2009 and 2011). If substantively small disadvantages persist over time, over an array of



public goods and services, inequity accrues and we see larger, persistent injustice. This is particularly true for assets like trees that appreciate in value over time. Although newly planted trees have small immediate impacts on tree canopy cover, they provide increasing benefits over time as the trees grow. For instance, in Atlanta, an American beech (*Fagus grandifolia*) planted at 1 in. (2.56 cm) in diameter provides only US\$2 of benefits per year initially; but that same tree at full size (24 in. in diameter) will provide over US\$200 per year in benefits (National Tree Benefits Calculator: <http://www.treebenefits.com>). In this way, small yet persistent injustices in tree-planting activities may lead to magnified injustices in the benefits of trees secured for communities in the future.

It is important to note that this article describes the outcomes of nonprofit activities, but does not describe the intentions or decisions of the organizations. As discussed above, project locations can be the result of many factors, including resident interest and characteristics of the built environment. Each neighborhood and community group engaging in planting is different, with different history, demographics, dynamics, and motivations; motivations for engaging in tree planting likely differ within cities as well as across nonprofits.

The findings of this study yield implications for practice and for theory and research. First, they suggest that a community-oriented model of planting might more successfully reach low canopy and low-income neighborhoods. Second, they reveal the need to identify and address barriers to participation in minority neighborhoods. For example, if future research found that fewer planting activities in certain neighborhoods resulted from systematic differences in nonprofit selection of applications or projects, then efforts to remedy inequity should target the application and decision-making process (perhaps by providing grants or other support to smaller nonprofits that operate in low-income areas). However, if lower planting instead stems from lack of neighborhood knowledge about the program or low capacity to apply, then nonprofits can target efforts to improve outreach and application assistance in minority communities. If lower planting comes from concern about trees or lack of interest, then the nonprofit might work to identify and alleviate concerns about trees. Strategies might include increasing maintenance activities for existing trees (or working with municipalities to do so) in minority neighborhoods to reduce risks, selecting trees to better fit the needs of neighbors, or providing information to neighbors about tree benefits and tree maintenance. Ultimately, nonprofits might be able to increase equity in planting by undertaking different strategies in different types of neighborhoods (see Locke & Grove, 2014, for a similar suggestion).

Differences between the results in this article and previous work raise questions about the causes of variation in tree-planting distribution.

Programmatic differences (e.g., in funding) and differences across cities might explain variation in distributional outcomes. Future undertakings should attempt to link variation in city and program context to distributional outcomes. In addition to considering municipalities and large citywide non-profit organizations, work along this line of inquiry might consider the impacts of smaller, neighborhood or community-based tree-planting groups that target their efforts in lower resource neighborhoods.

Finally, our inclusion of indicators of race and ethnicity revealed important information about the distributional patterns of tree-planting programs. These findings suggest race and ethnicity are related not only to historical patterns of land use but also to current drivers of urban development. Significant interaction effects reveal that race and ethnicity play different roles in different types of neighborhoods. Race and ethnicity should be included in future investigations of both municipal and nonprofit programs.

### **Acknowledgments**

The authors thank several colleagues for their comments on previous versions of this article: Burney Fischer, Matthew Baggetta, Ed Gerrish, Ken Richards, Kosali Simon, and three anonymous reviewers. Sarah Widney provided assistance with analysis in iTree Streets, and Paul McCord provided assistance with analysis in ArcGIS. The authors thank the nonprofit organization partners who generously shared their data and their experiences: The Greening of Detroit, Keep Indianapolis Beautiful, Inc., Pennsylvania Horticultural Society, Trees Atlanta, and Forest ReLeaf of Missouri. The authors are also grateful to the Alliance for Community Trees for supporting this research. Administrative support for this project was provided by the Center for the Study of Institutions, Population, and Environmental Change (CIPEC); the Vincent and Elinor Ostrom Workshop in Political Theory and Policy Analysis; and the Indiana University School of Public and Environmental Affairs. The authors are grateful to Julie England and Joanna Broderick for providing technical and writing expertise via CIPEC. This research was carried out while authors S.L.W, S.K.M, and J.M.V were researchers with the Bloomington Urban Forestry Research Group at Indiana University.

### **Authors' Note**

This research fulfilled part of the dissertation requirements of the School of Public and Environmental Affairs at Indiana University for S.L.W. Data and code are available upon request from author S.L.W.

### **Declaration of Conflicting Interests**

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

## Funding

The author(s) disclosed receipt of the following financial support for the research, authorship, and/or publication of this article: This article is part of a research project funded by the National Urban and Community Forestry Advisory Council of the U.S. Forest Service (USFS) and the USFS Northern Research Station, with additional financial support provided by the Efromson Family Fund, the State of Indiana Department of Natural Resources, the Garden Club of America, and the Indiana University Office of Sustainability.

## References

- Berman, M. G., Jonides, J., & Kaplan, S. (2008). The cognitive benefits of interacting with nature. *Psychological Science, 19*, 1207-1212.
- Bogar, S., & Beyer, K. M. (2015). Green Space, violence, and crime: A systematic review. *Trauma, Violence, & Abuse, 17*, 160-171. doi:10.1177/1524838015576412
- Bowen, W. (2002). An analytical review of environmental justice research: What do we really know? *Environmental Management, 29*, 3-15.
- Bowler, D. E., Buyung-Ali, L. M., Knight, T. M., & Pullin, A. S. (2010). A systematic review of evidence for the added benefits to health of exposure to natural environments. *BMC Public Health, 10*, 456-465.
- Bratman, G. N., Daily, G. C., Levy, B. J., & Gross, J. J. (2015). The benefits of nature experience: Improved affect and cognition. *Landscape and Urban Planning, 138*, 41-50.
- Buckley, G. L. (2010). *America's forest legacy: A century of saving trees in the old line state*. Santa Fe, New Mexico: Center for American Places.
- Cappiella, K., Schueler, T., & Wright, T. (2005). *Urban watershed forestry manual part 1: Increasing forest cover in a watershed*. NA-TP-04-05 Northeastern Area State and Private Forestry. Ellicott City, MD: U.S. Department of Agriculture Forest Service.
- Checker, M. (2011). Wiped out by the "Greenwave": Environmental gentrification and the paradoxical politics of urban sustainability. *City & Society, 23*, 210-229.
- Comber, A., Brunson, C., & Green, E. (2008). Using a GIS-based network analysis to determine urban greenspace accessibility for different ethnic and religious groups. *Landscape and Urban Planning, 86*, 103-114.
- Conway, T. M., & Bang, E. (2014). Willing partners? Residential support for municipal urban forestry policies. *Urban Forestry & Urban Greening, 13*, 234-243.
- Danford, R. S., Cheng, C., Strohbach, M. W., Ryan, R., Nicolson, C., & Warren, P. S. (2014). What does it take to achieve equitable urban tree canopy distribution? A Boston case study. *Cities and the Environment, 7*(1), Article 2.
- Donovan, G. H., & Butry, D. T. (2010). Trees in the city: Valuing street trees in Portland, Oregon. *Landscape and Urban Planning, 94*, 77-83.
- Donovan, G. H., & Mills, J. (2014). Environmental justice and factors that influence participation in tree planting programs in Portland, Oregon, U.S. *Arboriculture & Urban Forestry, 40*, 70-77.

- Donovan, G. H., & Prestemon, J. P. (2010). The effect of trees on crimes in Portland, Oregon. *Environment and Behavior, 44*, 3-30.
- Duinker, P., Steenberg, J., Ordóñez, C., Cushing, S., & Perfitt, K. R. (2014). Governance and urban forests in Canada: Roles of non-government organizations. *Proceedings of the Trees, People, and the Built Environment II* (pp. 151-159). Edgbaston, UK: Institute of Chartered Foresters.
- Escobedo, F. J., Kroeger, T., & Wagner, J. E. (2011). Urban forests and pollution mitigation: Analyzing ecosystem services and disservices. *Environmental Pollution, 159*, 2078-2087.
- Flocks, J., Escobedo, F., Wade, J., Varela, S., & Wald, C. (2011). Environmental justice implications of urban tree cover in Miami-Dade County, Florida. *Environmental Justice, 4*, 125-134.
- Grove, J. M., Locke, D. H., & O'Neil-Dunne, J. P. M. (2014). An ecology of prestige in New York City: Examining the relationships among population density, socio-economic status, group identity, and residential canopy cover. *Environmental Management, 54*, 402-419.
- Haluza, D., Schönbauer, R., & Cervinka, R. (2014). Green perspectives for public health: A narrative review on the physiological effects of experiencing outdoor nature. *International Journal of Environmental Research and Public Health, 11*, 5445-5461.
- Hartig, T., Mitchell, R., De Vries, S., & Frumkin, H. (2014). Nature and health. *Annual Review of Public Health, 35*, 207-228.
- Heynen, N. C., Perkins, H. A., & Roy, P. (2006). The political ecology of uneven urban green space: The impact of political economy on race and ethnicity in producing environmental inequality in Milwaukee. *Urban Affairs Review, 42*, 3-25.
- Hill, E., Dorfman, J. H., & Kramer, E. (2010). Evaluating the impact of government land use policies on tree canopy coverage. *Land Use Policy, 27*, 407-414.
- Jennings, V., & Gaither, C. J. (2015). Approaching environmental health disparities and green spaces: An ecosystem services perspective. *International Journal of Environmental Research and Public Health, 12*, 1952-1968.
- Jensen, R., Gatrell, J., Boulton, J., & Harber, B. (2004). Using remote sensing and geographic information systems to study urban quality of life and urban forest amenities. *Ecology and Society, 9*(5), 5.
- Joassart-Marcelli, P. (2010). Leveling the playing field? Urban disparities in funding for local parks and recreation in the Los Angeles region. *Environment and Planning A, 42*, 1174-1192.
- Kondo, M. C., Low, S. C., Henning, J., & Branas, C. C. (2015). The impact of green stormwater infrastructure installation on surrounding health and safety. *American Journal of Public Health, 105*(3), e114-e121.
- Krause, R. M. (2011). An assessment of the greenhouse gas reducing activities being implemented in the US cities. *Local Environment, 16*, 193-211.
- Kuo, F. E. (2001). Coping with poverty: Impacts of environment and attention in the inner city. *Environment and Behavior, 33*, 5-34.

- Kuo, F. E., Bacaicoa, M., & Sullivan, W. C. (1998). Transforming inner-city landscapes: Trees, sense of safety, and preference. *Environment and Behavior, 30*, 28-59.
- Kuo, F. E., & Sullivan, W. C. (2001). Environment and crime in the inner city: Does vegetation reduce crime? *Environment and Behavior, 33*, 343-367.
- Kweon, B.-S., Sullivan, W. C., & Wiley, A. R. (1998). Green common spaces and the social integration of inner-city older adults. *Environment and Behavior, 30*, 832-858.
- Landry, S. (2013). *Connecting pixels to people: Management agents and social-ecological determinants of changes to street tree distributions* (Graduate theses and dissertations). Retrieved from <http://scholarcommons.usf.edu/etd/4715>
- Landry, S. M., & Chakraborty, J. (2009). Street trees and equity: Evaluating the spatial distribution of an urban amenity. *Environment and Planning A, 41*, 2651-2670.
- Lee, A. C. K., & Maheswaran, R. (2011). The health benefits of urban green spaces: A review of the evidence. *Journal of Public Health, 33*, 212-222.
- Locke, D. H., & Grove, J. M. (2014). Doing the hard work where it's easiest? Examining the relationships between urban greening programs and social and ecological characteristics. *Applied Spatial Analysis and Policy, 1*-20.
- Lovasi, G. S., Quinn, J. W., Neckerman, K. M., Perzanowski, M. S., & Rundle, A. (2008). Children living in areas with more street trees have lower prevalence of asthma. *Journal of Epidemiology & Community Health, 62*, 647-649.
- Lyytimäki, J. (2014). Bad nature: Newspaper representations of ecosystem disservices. *Urban Forestry & Urban Greening, 13*, 418-424.
- McIntosh, C. S., & Dorfman, J. H. (1992). Qualitative forecast evaluation: A comparison of two performance measures. *American Journal of Agricultural Economics, 74*, 209-214.
- McPherson, E. G., & Ferrini, F. (2010, October 1). Trees are good, but. . . . *Arborist News*, pp. 58-60.
- McPherson, E. G., & Simpson, J. R. (2003). Potential energy savings in buildings by an urban tree planting programme in California. *Urban Forestry & Urban Greening, 2*, 73-86.
- McPherson, E. G., & Young, R. (2010). Understanding the challenges of municipal tree planting. *Arborist News, 19*(6), 60-62.
- Mincey, S. K., Hutten, M., Fischer, B. C., Evans, T. P., Stewart, S. I., & Vogt, J. M. (2013). Structuring institutional analysis for urban ecosystems: A key to sustainable urban forest management. *Urban Ecosystems, 16*, 553-571.
- Mincey, S. K., Schmitt-Harsh, M., & Thurau, R. (2013). Zoning, land use, and urban tree canopy cover: The importance of scale. *Urban Forestry & Urban Greening, 12*, 191-199.
- Mincey, S. K., & Vogt, J. M. (2014). Watering strategy, collective action, and neighborhood-planted trees: An Indianapolis case study. *Arboriculture and Urban Forestry, 40*, 84-95.
- Nowak, D. J. (1994). Understanding the structure. *Journal of Forestry, 92*(10), 42-46.
- Nowak, D. J., & Dwyer, J. F. (2007). Understanding the benefits and costs of urban forest ecosystems. In J. E. Kuser (Ed.), *Urban and community forestry in the Northeast* (2nd ed., pp. 25-46). New York: Springer.

- Nowak, D. J., & Greenfield, E. J. (2012). Tree and impervious cover change in U.S. cities. *Urban Forestry & Urban Greening*, *11*, 21-30.
- Pedlowski, M. A., Da Silva, V. A. C., Adell, J. J. C., & Heynen, N. C. (2002). Urban forest and environmental inequality in Campos dos Goytacazes, Rio de Janeiro, Brazil. *Urban Ecosystems*, *6*, 9-20.
- Perkins, H. A., Heynen, N., & Wilson, J. (2004). Inequitable access to urban reforestation: The impact of urban political economy on housing tenure and urban forests. *Cities*, *21*, 291-299.
- Pham, T. T. H., Apparicio, P., Séguin, A. M., Landry, S., & Gagnon, M. (2012). Spatial distribution of vegetation in Montreal: An uneven distribution or environmental inequity? *Landscape and Urban Planning*, *107*, 214-224.
- Pincetl, S. (2003). Nonprofits and park provision in Los Angeles: An exploration of the rise of governance approaches to the provision of local services. *Social Science Quarterly*, *84*, 979-1001.
- Ringquist, E. J. (2005). Assessing evidence of environmental inequities: A meta-analysis. *Journal of Policy Analysis and Management*, *24*, 223-247.
- Rosenzweig, C., Solecki, W., Parshall, L., Gaffin, S., Lynn, B., Goldberg, R., . . . Hodges, S. (2006). *Mitigating New York City's heat island with urban forestry, living roofs, and light surfaces* (New York City regional heat island initiative final report 06-06). Albany: New York State Energy Research and Development Authority.
- Schwarz, K., Fragkias, M., Boone, C. G., Zhou, W., McHale, M., Grove, J. M., . . . Cadenasso, M. L. (2015). Trees grow on money: Urban tree canopy cover and environmental justice. *PLoS ONE*, *10*(4), 1-17.
- Shanahan, D. F., Fuller, R. A., Bush, R., Lin, B. B., & Gaston, K. J. (2015). The health benefits of urban nature: How much do we need? *BioScience*, *65*, 476-485.
- Sullivan, W. C., Kuo, F. E., & DePooter, S. F. (2004). The fruit of urban nature: Vital neighborhood spaces. *Environment and Behavior*, *36*, 678-700.
- Taylor, A. F., Kuo, F. E., & Sullivan, W. C. (2001). Coping with ADD: The surprising connection to green play settings. *Environment and Behavior*, *33*, 54-77.
- Tibbetts, J. (2002). Building awareness of the built environment. *Environmental Health Perspectives*, *110*, 670-673.
- Troy, A. R., Grove, J. M., O'Neil-Dunne, J. P. M., Pickett, S. T. A., & Cadenasso, M. L. (2007). Predicting opportunities for greening and patterns of vegetation on private urban lands. *Environmental Management*, *40*, 394-412.
- Tyrväinen, L., & Miettinen, A. (2000). Property prices and urban forest amenities. *Journal of Environmental Economics and Management*, *39*, 205-223.
- Ulrich, R. S. (1979). Visual landscapes and psychological well-being. *Landscape Research*, *4*(1), 17-23.
- Ulrich, R. S. (1981). Natural versus urban scenes: Some psychophysiological effects. *Environment and Behavior*, *13*, 523-556.
- Ulrich, R. S. (1984). View through a window may influence recovery from surgery. *Science*, *224*, 420-421.
- van den Berg, A. E., Maas, J., Verheij, R. A., & Groenewegen, P. P. (2010). Green space as a buffer between stressful life events and health. *Social Science & Medicine*, *70*, 1203-1210.

- Ward Thompson, C., Roe, J., Aspinall, P., Mitchell, R., Clow, A., & Miller, D. (2012). More green space is linked to less stress in deprived communities: Evidence from salivary cortisol patterns. *Landscape and Urban Planning, 105*, 221-229.
- Widney, S. E., Vogt, J., & Fischer, B. C. (2015, March 21). *Survival, growth rate, and benefits of recently planted urban trees*. Presented at the 130th Annual Academy Meeting of the Indiana Academy of Science, Indianapolis IN.
- Wilson, J. S., & Lindsey, G. H. (2009). Identifying urban neighborhoods for tree canopy restoration through community participation. In J. D. Gatrell & R. R. Jensen (Eds.), *Planning and socioeconomic applications, geotechnologies and the environment* (Vol. 1, pp. 29-42). New York: Springer.
- Wolch, J. R., Byrne, J., & Newell, J. P. (2014). Urban green space, public health, and environmental justice: The challenge of making cities “just green enough.” *Landscape and Urban Planning, 125*, 234-244.
- Wolch, J. R., Wilson, J. P., & Fehrenbach, J. (2005). Parks and park funding in Los Angeles: An equity-mapping analysis. *Urban Geography, 26*, 4-35.
- Wolf, K. (2003). Public response to the urban forest in inner-city business districts. *Journal of Arboriculture, 29*, 117-126.
- Xiao, Q., McPherson, E. G., Ustin, S. L., Grismer, M. E., & Simpson, J. R. (2000). Winter rainfall interception by two mature open-grown trees in Davis, California. *Hydrological Processes, 14*, 763-784.
- Young, R. F., & McPherson, E. G. (2013). Governing metropolitan green infrastructure in the United States. *Landscape and Urban Planning, 109*, 67-75.

## Author Biographies

**Shannon Lea Watkins** is a postdoctoral research fellow in the Department of Geography and Environment at San Francisco State University. Her research examines urban social-ecological systems, community engagement, and environmental equity and justice.

**Sarah K. Mincey** is a social-ecological systems scientist who studies community-based natural resource management and environmental governance, with particular emphasis on urban forest ecology and management. In her current role as faculty at the School of Public and Environmental Affairs at Indiana University (IU), she serves as the associate director for the Integrated Program in the Environment and administrative director for the IU Research and Teaching Preserve.

**Jess Vogt** researches cities and neighborhoods as social-ecological systems, and in particular the community and biophysical outcomes of neighborhood and nonprofit tree planting. She is an assistant professor in the Department of Environmental Science and Studies at DePaul University College of Science and Health.

**Sean P. Sweeney** is a geographic information systems/remote sensing specialist in the Center for the Study of Institutions, Population, and Environmental Change at Indiana University.