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The politics of urban trees: Tree planting is associated with gentrification in Portland, Oregon

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A B S T R A C T

This study evaluated the hypothesis that urban-tree planting increases neighborhood gentrification in Portland, Oregon. We defined gentrification as an increase in the median sales price of single-family homes in a Census tract compared to other tracts in the city after accounting for differences in the housing stock such as house size and number of bathrooms. We used tree-planting data from the non-profit Friends of Trees, who have planted 57,985 yard and street trees in Portland (1990–2019). We estimated a mixed model of gentrification (30 years and 141 tracts) including random intercepts at the tract level and a first-order auto-regressive residual structure. Tract-level house prices and tree planting may be codetermined. Therefore, to address potential endogeneity of tree planting in statistical modeling, we lagged the number of trees planted by at least one year. We found that the number of trees planted in a tract was significantly associated with a higher tract-level median sales price, although it took at least six years for this relationship to emerge. Specifically, each tree was associated with a \$131 (95% CI: \$53–\$210; p-value $= 0.001$) increase in tract-level median sales price six years after planting. The magnitude of the association between the number of trees planted and median sales price generally increased as the time lag lengthened. After twelve years, each tree was associated with a \$265 (95% CI: \$151–\$379; p-value<0.001) increase in tract-level median sales price. Tree planting was not merely a proxy for existing tree cover, as the percent of a tract covered in tree canopy was independently associated with an increase in median sales price. Specifically, each 1-percentage point increase in tree-canopy cover was associated with a \$882 (95% CI: \$226–\$1538; p-value $= 0.008$) increase in median sales price. In conclusion, tree planting is associated with neighborhood-level gentrification, although the magnitude of the association is modest.

1. Introduction

Many US cities have explicit tree-planting goals. For example, in 2006, Los Angeles launched an initiative to plant one million trees (Pincetl, 2010), and New York adopted a similar plan in 2007 (Morani et al., 2011). A major impetus for these and other similar programs is the ecosystem services that urban trees provide including improved air quality (Nowak et al., 2006), reduced storm-water runoff (Berland et al., 2017), lower crime (Kuo and Sullivan, 2001), and improved public health (Donovan et al., 2011). However, one possible consequence of urban-tree planting, that has received less attention, is gentrification. Although, to our knowledge, no studies have shown that urban-tree planting can cause gentrification, several studies have shown that gentrification is associated with large green infrastructure projects including the BeltLine in Atlanta (Immergluck and Balan, 2017) and the 606 rails-to-trails project in Chicago (Rigolon and Németh, 2018). To address this gap in the literature, we assess whether 30 years of urban-tree planting is associated with gentrification in Portland, Oregon (Multnomah County).

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1.1. Literature review

There is not a single accepted definition of gentrification, but it's generally considered to be an influx of more affluent residents that causes changes in the demographic composition and character of a neighborhood (Freeman, 2009; Lopez-Morales, 2011). Changes may additionally include increased property values and new types of businesses (Lees et al., 2013). Because gentrification lacks a single definition, may studies use multiple gentrification metrics (Anguelovski et al., 2017; Immergluck and Balan, 2017).

However defined, gentrification is a major public-policy issue. The effects of urban renewal on gentrification are a particular concern (Uzun, 2003). Large urban-renewal projects must often demonstrate how they will avoid, or at least ameliorate, gentrification (Uitermark and Loopmans, 2013). Many city governments have departments or programs focused on avoiding gentrification. For example, in Portland, Oregon, where this study takes place, the city commissioned a study that classified neighborhood-gentrification risk on a six-point scale (Bates, 2013). The city uses this typology when considering projects with the potential to cause gentrification.

Green gentrification is a form of gentrification that is driven by improvements to a neighborhood's natural amenities such as parks, trails, and trees (Gould and Lewis, 2016). Several studies have examined the issue of green gentrification from a qualitative perspective (Anguelovski, 2016; Curran and Hamilton, 2012; Gould and Lewis, 2012), but fewer studies have identified and quantified specific examples of green gentrification. This is perhaps not surprising, given that major changes to a city's natural amenities are relatively rare.

Anguelovski et al. (2017) studied the impact of creating 18 new parks in Barcelona in the 1990s and early 2000s. Using six gentrification metrics (house prices, % residents with a degree, % residents >65 years old, % immigrants from Global South, % immigrants from Global North, household income), the authors found that in central Barcelona new parks were associated with increased gentrification. However, in more economically depressed neighborhoods, away from the city center, parks were associated reverse gentrification (% residents with a degree declined). Immergluck and Balan (2017) examined the impact of the Atlanta BeltLine, which is a 22-mile loop of parks around the city. After construction began, real-estate prices within half a mile of the project increased 18–27% compared to other areas of the city. The authors note that many realtors emphasize proximity to the BeltLine in their marketing materials, and several real-estate companies focus exclusively on adjacent neighborhoods. Rigolon and Németh (2018) focused on effects of the 606 rails-to-trails project, which broke ground in Chicago in 2013. Between 2010 and 2016, median household income, percent of residents with a bachelor's degree, percent white residents, and average rent all increased faster in neighborhoods adjoining the trail than the rest of Chicago. These changes led to protests by residents of affected neighborhoods. Non-profit organizations were heavily involved in the implementation of the 606 project, which had some disadvantages, as these organizations had a narrow focus that did not include other issues such as affordable housing. Merse et al. (2009) examined how the Bolton Hill neighborhood in Baltimore used tree planting as an urban-renewal tool. Beginning in 1963, trees were planted by both city government and nonprofit groups. These programs expanded to include tree maintenance and surveys. The neighborhood was able to increase its canopy cover while the city as a whole lost trees. Although the authors don't conduct any analysis of the impacts of tree planting, they do note that house prices in Bolton Hill rose steeply in the 1990s and early 2000s.

Several studies have shown that urban-tree canopy cover is associated with the racial composition and socio-economic status of a neighborhood. For example, a study in Atlanta (Koo et al., 2019) found that, in 2000, neighborhoods with less trees had a higher proportion of African American residents, had lower median household income, and had a higher proportion of renters. The authors repeated the analysis in 2013; they still found an association between tree cover, income, and percent renters; however, they no longer found that tree cover was associated with the racial composition of a neighborhood. Results show that the association between trees, race, and socioeconomic status may change over time. Jesdale et al. (2013) examined the relationship between race, socioeconomic status, and exposure to high temperatures. Using the 2000 Census and the 2001 National Landcover Database, they defined heat-risk related landcover as landcover that consisted of less than 50% tree cover and more than 50% impervious surface. Results showed that non-Hispanic whites had the lowest risk of being exposed to heat-risk related landcover compared to all other racial groups.

Several studies have examined the racial and socioeconomic composition of neighborhoods in which nonprofits plant trees. For example, Watkins et al. (2016) studies the tree planting of four US nonprofits. These groups were less likely to plant trees in Census-block groups that had higher existing tree cover and higher household income. However, the nonprofits were also less likely to plant trees in block groups that had more African American or Hispanic residents. Donovan and Mills (2014) analyzed the factors that influenced whether residents agreed to participate in a tree-planting programs. Residents with existing street trees and older homes were more likely to participate in the program, whereas residents who had lived in their homes for longer, or lived in neighborhoods with a lower high-school graduation rate, were less likely to participate in the program.

Finally, multiple studies have found a positive association between the sales price of homes and yard trees (Anderson and Cordell, 1988), street trees (Donovan and Butry, 2010), trees in the surrounding neighborhood (Donovan and Butry, 2011; Escobedo et al., 2015), and proximity to forest land (Tyrvainen and Miettinen, 2000).

2. Materials and methods

2.1. Data and study area

Portland is the largest city in Oregon, with a population of 654,741; 70.5% of residents are non-Hispanic white, 5.8% are black, 8.1% are Asian, and 9.7% are Hispanic (US Census, 2019). Between 2014 and 2018, 53.1% of residents live in owner-occupied homes; the median value of owner-occupied homes was $383,600 (2018 dollars); median residential rent was $1187 (2018 dollars) (US Census, 2019). Fig. 1 shows the location of Portland as well as 2010 Census-tract boundaries.

We characterized gentrification as changes in the sales price of single-family homes at the Census-tract level. We chose this definition for two reasons. First, in contrast to changes in demographic composition, sales-price data were available annually, so we could longitudinally study the drivers of gentrification. In contrast, Census data, which previous studies have relied on, are only available every 5–10 years. Second, multiple studies have shown that other elements of gentrification—changes in racial composition, for example—are mediated, at least in part, by changes in house prices (Lopez-Morales, 2011). Therefore, changes in house prices may be a good metric despite gentrification being a complex and multi-faceted process (Guerrieri et al., 2013).

Past studies of Portland, Oregon, have defined gentrification using the median sales price of homes at the neighborhood level (Bates, 2013). However, this approach does not account for differences in the housing stock. Average house size may differ across neighborhoods, for example. Therefore, for each year of the study period (1990–2019), we first estimated a hedonic model in which the natural logarithm of house price was regressed against the physical characteristics of the house and the season in which a sale took place (we were limited to the physical characteristics routinely collected by Multnomah County). In addition, we included random effects at the Census-tract level ($n = 141$ tracts). A tract was included in the analysis if at least 50% of a tract's area fell within Portland City limits (the number of tracts roughly corresponds to the 130 named neighborhoods in Portland):

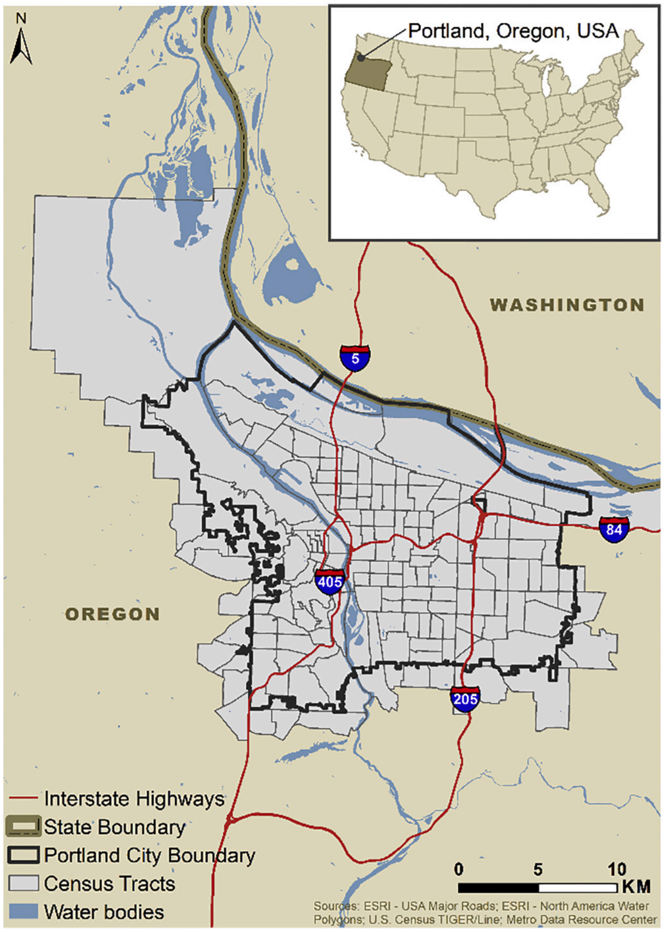

Fig. 1. Portland, Oregon showing 2010 Census tracts and city boundary.

$$lnP_{i,j} = B_0 + B_1 Ln(House\ area)_{i,j} + B_2 Ln(Lot\ area)_{i,j} + B_3 House\ age_{i,j} + B_4 Bathrooms_{i,j} + B_{5-7} Season\ of\ sale_{i,j} + B_{8-14} Heating\ system_{i,j} + u_j + e_i$$

The subscript i denotes houses, the subscript j denotes Census tracts, B_{5-7} are coefficients on dummy variables denoting the season of sale (spring omitted), B_{8-14} are coefficients on dummy variables denoting a house's heating and cooling system (baseboard omitted) (past studies in Portland have found that heating and cooling systems were significantly associated with the sale price of single-family homes (Donovan and Butry, 2010)), u_j are tract-level random effects, and e_i are i.i.d. error terms. The tract-level random effects (u_j) capture differences in neighborhood desirability after controlling for differences in house characteristics. Therefore, we used these random effects as our metric of gentrification. A positive random effect indicates that a tract is more desirable than average, whereas a negative random effect indicates that a tract is less desirable than average. For ease of interpretation, we back-transformed the random effects to dollars and discounted all values to 2019 dollars using the consumer-price index (this back-transformation took place at median sales price for each year). We estimated a separate hedonic model for each year of the study, which resulted in a panel data set of gentrification metrics (30 years and 141 Census tracts). We obtained data on house characteristics and sales prices from Multnomah County's Tax Assessors Office.

We used tree-planting data from Friends of Trees, which is a Portland based non-profit. Between 1990 and 2019, they planted 57,985 trees in private yards and parking strips (the grass strip between the road and the sidewalk) in Portland. Friends of Trees plants trees in response to requests from individuals. In addition, they mount tree-planting campaigns focused on neighborhoods that have below average tree canopy. These campaigns involve direct mail as well as in-person canvassing. Since 1990, they have planted trees in 136 of the 141 tracts in our analysis. Friends of Trees has a separate tree-planting program that focuses on natural areas and parks. We did not include these trees in our analysis. Depending on species, trees were four to eight years old when planted. To ensure that the number of trees planted was not merely a proxy for existing tree cover, we calculated tract-level tree-canopy cover using 1 m-resolution classified aerial imagery from the US EPA's EnviroAtlas (Agency, 2012). The correlation coefficient between existing tree cover and number of trees planted was −0.16.

Affluent home buyers may be attracted to a neighborhood by the opportunity to renovate older, poorly-maintained houses (Lopez-Morales, 2011). Therefore, we calculated mean house age, mean house size, and mean lot size in a tract.

Light rail has been associated with both gentrification and reverse gentrification (Baker and Lee, 2019). Therefore, we accounted for the number of light-rail stops in a tract. Since 1986, Portland has built five light-rail lines, two of which (red and blue) opened in two phases. The location of light-rail lines and stops were publicly announced 4–8 years in advance of lines opening.

Based on past research (Cebula, 2009), we hypothesized that tracts with historic significance might be more desirable and prone to gentrification. We accounted for historic significance in two ways. First, we used a dummy variable to denote whether a tract contained one of Portland's 15 historic districts. An historic district can be designated by the City of Portland or may be a national-register district listed on the National Register of Historic Places. Second, we accounted for the number of historic landmarks in a tract. As with historic districts, landmarks can be declared by the city or listed on the National Register of Historic Places.

Parks have been associated with gentrification in previous studies (Anguelovski et al., 2017). Therefore, we calculated the total area of parkland in each tract as well as the proportion of each tract covered by parkland.

Table 1 shows data sources for all variables.

2.2. Statistical analysis

We estimated a mixed model of neighborhood desirability in which the dependent variable was the random effects from the 30 first-stage hedonic models described above. In addition to number of trees planted, covariates included housing characteristics (mean house size, for

Table 1
Data sources.

Data	Data Sources
Census tract boundaries	"2010 TIGER/Line Census Tract shapefiles" U.S. Census Bureau. Date: 2010
Geocoded addresses	"2019 TIGER/Line All Lines (edges) shapefiles" Prepared by the U.S. Census Bureau. Date: 2019.
Historic districts	"Historic Districts" City of Portland, Bureau of Planning and Sustainability. Publication date: 03/25/2013. Last update: 05/04/2020.
Historic landmarks	"Historic landmarks" City of Portland, Bureau of Planning and Sustainability. Publication date: 4/19/2013. Last update: 5/12/2020.
Parks	"Parks" City of Portland, Bureau of Parks and Recreation. Publication date: 01/01/2002. Last update: 01/23/2020.
Tree cover	"EviroAtlas – Portland, OR – Meter-scale Urban Land Cover (MULC) Data (2012)" U.S. Environmental Protection Agency (EPA), Office of Research & Development (ORD) – National Exposure Research Laboratory (NERL). Publication date: 10/28/2014.
Light-rail stops	"Trimet Stops (Route Stops)" Trimet GIS. Last updated: 04/07/2020.
Sales data and house characteristics	Multnomah County, Taxation and Assessment. Received 04/24/2020. Data available on request from authors.

example), historic districts and landmarks, light-rail stops, and tree-canopy cover:

$$Neighborhood\ Desirability_{i,j} = B_0 + B_1 Trees\ planted_{i,j} + \boldsymbol{BX} + u_i + e_{i,j}$$

where i denotes Census tracts (141 tracts); j denotes years (1990–2019); $\boldsymbol{X}$ is a vector of covariates and $\boldsymbol{B}$ is a vector of associated regression coefficients; u_i are tract-level random effects; $e_{i,\ j}$ are error terms. The mean size of a census tract is 256 ha (SD = 449 ha).

Tree planting and gentrification may be codetermined: tree planting may cause gentrification, but gentrifying neighborhoods may also be more likely to plant trees. In particular, several studies have shown that people are most likely to plant a trees when they first move into a house (Donovan and Mills, 2014), and gentrification, by definition, involves an influx of new residents. Therefore, any regression model of neighborhood desirability and tree planting may suffer from endogeneity (Greene, 2000). Specifically, the number of trees planted may be correlated with model residuals. To address this issue, we lagged the number of trees planted by at least one year (neighborhood desirability in the current year is regressed against tree planting in the previous, or earlier, years). This prevents reverse causation, as neighborhood desirability cannot causally influence the number of trees planted in previous years. In addition, as a practical matter, trees that have just been planted may be too small to positively influence neighborhood desirability and cause gentrification. Therefore, we tested several lag lengths of the number of trees planted to determine whether there is a minimum age threshold below which trees are not associated with changes in neighborhood desirability.

The dependent variable in the second-stage model of gentrification, neighborhood desirability, was estimated in a series of first-stage hedonic models. While measurement error in independent variables can lead to biased coefficient estimates, measurement error in the dependent variable only reduces the precision of coefficient estimates and lowers t-statistics (assuming classical assumptions are met) (Hausman, 2001). However, when variables are estimated with uneven samples sizes, leading to unequal sampling variance, then heteroscedasticity can result (in our case, house sales were not evenly distributed across Census tracts) (King, 2013). Therefore, we used the Huber-White sandwich estimator to estimate standard errors.

During parts of our study period (particularly since 2010), house prices increased faster than inflation, so our gentrification metrics trended upwards over time. To account for this non-stationarity, we included a categorical year variable in our model. We chose to represent time categorically to avoid an assumption of a linear independent relationship between neighborhood desirability and time.

Different instances of neighborhood desirability within a Census tract are not temporally independent. For example, if neighborhood desirability is above average in a tract, for a given year, then it is likely to be above average the following year. To address this temporal autocorrelation, we included a within-tract autoregressive residual structure. We chose to address temporal autocorrelation in the random part of the model, rather than by including a lag of the dependent variable as an explanatory variable, because a lagged dependent variable would have introduced measurement error into the right-hand side of the model, which could result in biased coefficient estimates (Hausman, 2001).

To determine whether the association between tree planting and neighborhood desirability was consistent across the sample, we conducted two stratified analyses based on the number of non-Hispanic white residents and mean household income in the 2010 Census. In the stratified models, we included an interaction term between trees planted and a binary variable indicating whether either percent non-Hispanic white residents or mean household income was below or above the citywide mean. If this interaction term was significant ($p <$ 0.05), then that indicated the association between tree planting and neighborhood desirability was different in the two strata.

In addition, we estimated separate models on street trees and yard trees (the main model combined the two types of plantings). We estimated separate models for three reasons. First, we hypothesized that tree planting in the public right of way may have a different effect on neighborhood desirability than planting in private yards. Second, the species list that people can choose from is different for street and yard trees. Specifically, the street-tree list, that Friends of Trees allows residents to choose from, includes smaller species suitable for planting in narrow parking strips such as Japanese snowbell (*Styrax japonicas*), for example. In contrast, the yard-tree list contains more large, native species such as bigleaf maple (*Acer macrophyllum*), for example. Third, past research in Portland has found that street trees and yard trees have differential effects on house price (Donovan and Butry, 2010) and house rent (Donovan and Butry, 2011).

3. Results

From 1990 to 2019, 153,215 single-family homes sold in Portland (median sales price in 2019 dollars was $294,150). The minimum number of homes sold in a year was 1930 in 1991, and the maximum number was 9886 in 2019. Table 2 shows the regression coefficients and sample sizes for the 30 annual hedonic models (for space reasons, the coefficients for heating and cooling systems are not shown but are available from the authors). Results are largely consistent across the 30 years. For example, the coefficients on house size, lot size, and number of bathrooms are always positive. However, some variables are not consistently significant across all 30 years (number of bathrooms, for example). If these 30 models were run as OLS models without tract-level random effects, the mean R-squared was 0.28 (SD = 0.067).

Across the 30-year study period, neighborhood desirability was $232,132 higher in the most desirable tract compared to the least desirable tract. In other words, a house that sold for the median house price (median sales price across the entire city for a given year) in the least desirable tract (lowest tract-level random effect) would have sold for $232,132 more, if it had been located in the most desirable tract (highest tract-level random effect). The most desirable tract had a median household income of $99,039, 95% of residents were non-Hispanic white, 82% of homes were owner occupied, and 56% of the tract was covered by tree canopy. In contrast, in the least desirable tract, median household income was $35,402, 75% of residents were non-Hispanic white, 60% of homes were owner occupied, and 15% of the tract was covered by tree canopy.

Regression results of neighborhood desirability against tree planting are shown in Table 3. The year range is 1996–2019, because of the six-year lag on tree planting and the two-year lead on number of light-rail stops. None of the year indicator variables was significant (at the 5% level) until 2011, which suggests that, from 1996 to 2010, *ceteris paribus*, house-price increases in Portland roughly kept pace with inflation, whereas, after 2010, house prices increased faster than the rate of inflation. Having a light-rail stop in a tract was associated with higher neighborhood desirability. Interestingly, the presence of a light-rail stop became significant, on average, two years before opening, which corresponds roughly with the 2–4 year construction time of Portland's five light-rail lines (this excludes the blue line, which experienced construction delays due to tunneling difficulties). For example, the Green Line began construction in February 2007 and opened on September 12, 2009 (TriMet, 2020). Tracts that had at least one listing on the National Register of Historic Places were more desirable as were neighborhoods with larger and older homes. Finally, tracts with more tree cover were more desirable. Specifically, a 1-SD increase in tree cover was associated with a $11,727 increase in median sales price (mean tree cover for the city was 26.2% [SD = 13.3]). Note that the area of parks in a tract was not significantly associated with neighborhood desirability.

All else equal, tracts that had planted trees six years ago were more desirable. Specifically, each tree was associated with a $131 increase in median sale price with all other variables held constant. The mean annual number of trees planted per tract in the sample is 13.7 (SD =

Table 2
Regression coefficients, and associated 95% confidence intervals, for hedonic models of single-family home sales in Portland, Oregon (1990–2019).

Year	Sample size	# Bathrooms	95% CI	Year built	95% CI	ln(lot size)	95% CI
1990	2143	0.020	−0.019 to 0.059	0.00236	0.00136 to 0.00337	0.178	0.123 to 0.232
1991	1930	0.011	−0.043 to 0.066	0.00159	0.00026 to 0.00292	0.070	−0.005 to 0.146
1992	2186	−0.001	−0.037 to 0.034	0.00213	0.00125 to 0.00302	0.105	0.054 to 0.156
1993	2809	0.004	−0.036 to 0.043	0.00222	0.0012 to 0.00325	0.045	−0.006 to 0.096
1994	2743	0.040	0 to 0.081	0.00039	0.00021 to 0.00058	0.030	−0.027 to 0.086
1995	2607	0.021	−0.055 to 0.097	0.00363	0.00201 to 0.00524	0.081	−0.007 to 0.168
1996	3035	0.055	−0.012 to 0.122	0.00019	−0.0001 to 0.00049	0.022	−0.07 to 0.115
1997	2969	0.037	0.001 to 0.074	0.00129	0.0004 to 0.00217	0.051	0.005 to 0.097
1998	3590	0.039	0.01 to 0.069	0.00174	0.00103 to 0.00246	0.039	0.002 to 0.077
1999	3554	0.045	0.017 to 0.073	0.00025	0.00009 to 0.00041	0.038	−0.002 to 0.078
2000	3426	0.051	0.022 to 0.08	0.00088	0.00019 to 0.00157	0.063	0.022 to 0.103
2001	3960	0.055	0.024 to 0.086	−0.00031	−0.00099 to 0.00037	0.033	−0.007 to 0.074
2002	4330	0.050	0.025 to 0.074	−0.00085	−0.00142 to −0.00028	0.033	0.001 to 0.066
2003	5027	0.055	0.032 to 0.078	−0.00007	−0.00061 to 0.00046	0.091	0.061 to 0.122
2004	5505	0.043	0.021 to 0.065	0.00014	−0.00041 to 0.00069	0.062	0.031 to 0.094
2005	6283	0.050	0.034 to 0.067	−0.00035	−0.00046 to −0.00024	0.071	0.047 to 0.095
2006	5236	0.064	0.04 to 0.088	−0.00059	−0.00112 to −0.00006	0.054	0.022 to 0.086
2007	4790	0.063	0.038 to 0.088	−0.00108	−0.00164 to −0.00052	0.045	0.011 to 0.079
2008	3893	0.060	0.018 to 0.102	−0.00123	−0.00206 to −0.0004	0.052	0.002 to 0.102
2009	4109	0.047	0.013 to 0.081	−0.00072	−0.0014 to −0.00004	0.032	−0.011 to 0.076
2010	4055	0.074	0.037 to 0.11	−0.00154	−0.00227 to −0.00081	0.017	−0.028 to 0.062
2011	4210	0.074	0.045 to 0.104	0.00001	−0.00015 to 0.00017	0.105	0.068 to 0.142
2012	5418	0.043	0.012 to 0.073	0.00004	−0.00012 to 0.0002	0.015	−0.023 to 0.053
2013	6475	0.055	0.033 to 0.078	−0.00018	−0.00062 to 0.00027	0.081	0.052 to 0.11
2014	7071	0.064	0.044 to 0.084	−0.00014	−0.00055 to 0.00027	0.103	0.076 to 0.129
2015	8889	0.053	0.026 to 0.08	−0.00036	−0.0009 to 0.00018	0.058	0.024 to 0.093
2016	9243	0.060	0.038 to 0.082	−0.00049	−0.00094 to −0.00005	0.041	0.015 to 0.067
2017	9581	0.072	0.057 to 0.087	−0.00002	−0.00012 to 0.00009	0.099	0.081 to 0.118
2018	9483	0.075	0.061 to 0.09	0.00014	−0.00016 to 0.00044	0.107	0.089 to 0.125
2019	9886	0.112	0.1 to 0.124	0.00009	0.00001 to 0.00017	0.121	0.105 to 0.136

b

Year	ln(house size)	95% CI	Summer	95% CI	Fall	95% CI	winter	95% CI
1990	0.592	0.516 to 0.667	0.102	0.052 to 0.152	0.154	0.1 to 0.209	0.010	−0.049 to 0.069
1991	0.567	0.463 to 0.672	0.091	0.018 to 0.165	0.094	0.017 to 0.17	−0.023	−0.102 to 0.057
1992	0.534	0.466 to 0.602	0.029	−0.017 to 0.076	0.059	0.011 to 0.107	−0.041	−0.092 to 0.011
1993	0.595	0.514 to 0.676	0.051	−0.008 to 0.11	0.053	−0.006 to 0.112	−0.004	−0.066 to 0.059
1994	0.506	0.426 to 0.585	0.027	−0.028 to 0.082	0.038	−0.02 to 0.096	−0.027	−0.088 to 0.034
1995	0.575	0.427 to 0.723	−0.028	−0.132 to 0.076	−0.138	−0.243 to −0.033	−0.108	−0.224 to 0.007
1996	0.629	0.49 to 0.769	0.163	0.061 to 0.266	0.201	0.094 to 0.307	−0.050	−0.161 to 0.061
1997	0.518	0.444 to 0.593	0.014	−0.039 to 0.067	0.071	0.018 to 0.125	−0.009	−0.067 to 0.049
1998	0.459	0.398 to 0.52	0.037	−0.006 to 0.08	0.004	−0.04 to 0.048	−0.055	−0.103 to −0.008
1999	0.538	0.478 to 0.599	0.032	−0.01 to 0.074	0.024	−0.02 to 0.068	−0.026	−0.072 to 0.021
2000	0.501	0.44 to 0.562	0.021	−0.02 to 0.063	0.014	−0.029 to 0.057	−0.013	−0.06 to 0.034
2001	0.479	0.418 to 0.541	0.032	−0.009 to 0.073	0.045	0.001 to 0.089	−0.042	−0.088 to 0.004
2002	0.510	0.459 to 0.561	0.063	0.027 to 0.098	0.070	0.033 to 0.106	0.030	−0.007 to 0.068
2003	0.477	0.43 to 0.525	0.010	−0.022 to 0.042	0.020	−0.012 to 0.053	0.005	−0.032 to 0.041
2004	0.535	0.486 to 0.585	0.067	0.034 to 0.1	0.085	0.051 to 0.12	−0.001	−0.04 to 0.038
2005	0.467	0.429 to 0.504	0.047	0.022 to 0.071	0.076	0.05 to 0.102	−0.022	−0.05 to 0.006
2006	0.470	0.418 to 0.522	0.087	0.053 to 0.12	0.059	0.022 to 0.096	−0.026	−0.064 to 0.011
2007	0.478	0.424 to 0.532	0.030	−0.004 to 0.065	−0.029	−0.067 to 0.01	−0.071	−0.112 to −0.031
2008	0.537	0.451 to 0.622	0.003	−0.053 to 0.059	−0.065	−0.126 to −0.005	−0.090	−0.153 to −0.027
2009	0.491	0.422 to 0.559	0.040	−0.007 to 0.088	0.039	−0.008 to 0.087	−0.025	−0.081 to 0.031
2010	0.502	0.429 to 0.576	−0.066	−0.115 to −0.017	−0.066	−0.117 to −0.015	−0.100	−0.152 to −0.048
2011	0.480	0.415 to 0.545	−0.006	−0.049 to 0.037	−0.019	−0.063 to 0.026	−0.020	−0.066 to 0.027
2012	0.504	0.436 to 0.571	0.064	0.02 to 0.108	0.028	−0.017 to 0.073	−0.034	−0.084 to 0.016
2013	0.523	0.477 to 0.57	0.043	0.013 to 0.072	0.048	0.016 to 0.08	−0.059	−0.093 to −0.024
2014	0.442	0.399 to 0.484	0.030	0.001 to 0.058	0.018	−0.011 to 0.047	−0.032	−0.064 to −0.001
2015	0.495	0.438 to 0.552	0.021	−0.016 to 0.058	0.036	−0.003 to 0.075	0.002	−0.041 to 0.044
2016	0.420	0.373 to 0.467	0.059	0.028 to 0.089	0.036	0.005 to 0.067	−0.039	−0.072 to −0.006
2017	0.368	0.336 to 0.399	−0.001	−0.023 to 0.021	−0.020	−0.043 to 0.002	−0.065	−0.09 to −0.041
2018	0.350	0.321 to 0.379	−0.002	−0.021 to 0.018	−0.043	−0.064 to −0.022	−0.062	−0.084 to −0.04
2019	0.285	0.261 to 0.31	0.004	−0.014 to 0.023	−0.014	−0.033 to 0.005	−0.035	−0.056 to −0.015

20.4; maximum = 187), which corresponds to an increase in median sales price of $1797. The six-year lag on number of trees planted is not surprising, given that newly planted trees are unlikely to have an immediate effect on neighborhood desirability. We also investigated the effect of lengthening the lag on number of trees planted beyond six years. To do this, we first estimated a model with a 12-year lag on number of trees planted. We then estimated models with progressively shorter lags while holding the effective sample size constant—i.e., constraining them to use the same sample observations as the 12-year lag model (137 tracts; 2226 observations). Therefore, results reflect the effect of different lag lengths only (Ng and Perron, 2005), not affected by a changing sample of observations (although degrees of freedom may change) (Table 4). Shrinking the lag on tree planting from 12 to 6 years generally decreased the magnitude of the coefficient on the number of trees planted, although in year 7 and 10, the coefficients weren't significant. The positive relationship between magnitude of

Table 3
Association between neighborhood desirability and number of trees planted in Portland, Oregon from 1990 to 2019 (number of tracts = 138, number of observations = 2998). Mixed model with AR1 residual structure. Standard errors were estimated with the White-Huber estimator.

Variable	Coefficient	95% CI	Robust SE	*p*-value
Year (reference 1996)				
1997	6243	−628 to 13,114	3506	0.075
1998	4918	−1657 to 11,493	3355	0.143
1999	3394	−2113 to 8901	2810	0.227
2000	3957	−2830 to 10,744	3463	0.253
2001	2468	−3767 to 8703	3181	0.438
2002	2785	−3736 to 9306	3327	0.403
2003	5884	−3470 to 15,237	4772	0.218
2004	5691	−3280 to 14,662	4577	0.214
2005	8965	−2788 to 20,719	5997	0.135
2006	8352	−2583 to 19,288	5579	0.134
2007	8761	−4625 to 22,147	6830	0.200
2008	4696	−5994 to 15,386	5454	0.389
2009	10,692	−1479 to 22,863	6210	0.085
2010	7544	−3465 to 18,552	5617	0.179
2011	18,291	3395 to 33,187	7600	0.016
2012	18,067	2529 to 33,604	7927	0.023
2013	19,602	3675 to 35,530	8127	0.016
2014	24,092	6809 to 41,374	8818	0.006
2015	23,583	6575 to 40,591	8678	0.007
2016	23,143	5315 to 40,970	9096	0.011
2017	27,020	8625 to 45,414	−9385	0.004
# Light-rail stops (2-year lead)	5461	193to 10,730	−2688	0.042
NRHP (binary)	21,225	8165 to 34,284	6663	0.001
Tree cover (%)	882	226 to 1538	335	0.008
Mean house age (years)	398	157 to 640	123	0.001
Mean house size (m^2)	559	333 to 786	115	<0.001
# Trees planted (6-year lag)	**131**	**52.5 to 210**	**40.1**	**0.001**
Random-effects parameters				
Tract-level random intercept variance	7.93E+08	5.58E+09 to 1.13E+9	1.42E+08	
AR(1): rho	0.513	0.424 to 0.593	0.0432	
AR(1): within group error variance	1.95E+09	1.72E+09 to 2.21E+09	1.25E+08	

Table 4
Coefficients (and associated confidence intervals and *p*-values) on the number of trees planted with varying time-lag lengths (number of tracts = 137; number of observations = 2226).

Lag length	Coefficient	95% CI	*p*-value
1	2.8	−91.9-97.5	0.953
2	48.2	−34.9-131	0.256
3	32.2	−44.1-109	0.408
4	15.1	−73.9-104	0.739
5	51.5	−30.1-133	0.216
6	119	30.0–208	0.009
7	14.3	−69.9-98.5	0.739
8	150	72.2–227	<0.001
9	180	79.4–281	<0.001
10	70.3	−24.9-165	0.148
11	170	58.5–281	0.003
12	265	151–379	<0.001

effect and years since planting suggests that older, larger trees have a greater impact on gentrification than younger, smaller trees. Note that the coefficient on number of trees planted in Table 3 does not match the coefficient on number of trees planted (6-year lag) in Table 4, as these two models do not use the same sample. Fig. 2 shows examples of trees planted by Friends of Trees in 2008, 2014, and 2020.

To allow our results to be compared to the broader gentrification literature, we calculated the correlation between our gentrification metric and four demographic measures of gentrification: percent non-Hispanic white residents, percent of residents over 25 without a high-school diploma, median household income, and percent of homes that are owner occupied. We chose these four metrics, as race, education, income, and percent renters have all been used in previous studies of green gentrification. Data to calculate these metrics were not available for each year of the study period. Therefore, we calculated changes in these four metrics between the 1990 and 2010 Censuses, which we compared to changes in our measure of neighborhood desirability between 1990 and 2010 (Table 5). The sign of the correlation coefficients show that our measure of neighborhood desirability is consistent with other metrics of gentrification. The strongest correlations were with percent of residents who are non-Hispanic white and median household income. As Census data are only available for three of the 30 years of our study period, we were unable to estimate comparable gentrification models with demographic metrics as the dependent variable.

There was no significant difference in the coefficients on number of tree planted in tracts that had a below average percent of non-Hispanic white residents compared to tracts in which the percent of non-Hispanic white residents was above average. Similarly, the coefficient on number of trees planted didn't vary significantly between high- and low-income tracts. However, when we estimated separate models for street trees and yard trees (12.5% of trees planted by Friends of Trees were yard trees), we found that the magnitude of the association between tree planting and neighborhood desirability was roughly triple for yard trees compared to street trees (Table 6). This suggests that yard trees may have a greater impact on gentrification than street trees.

4. Discussion

We found that tree planting by the non-profit organization Friends of Trees was associated with gentrification at the Census-tract level. However, the magnitude of the effect was modest. The average size of a planting was 27.7 trees (SD = 25.2), and a tree planting of this size was associated with an increase in median sales price of $3569 (1.2% of the median sales price [$294,150 in 2019 dollars] for the study period). The largest tree planting conducted by Friends of Trees (187 trees) was associated with a $24,534 increase in median sales price (8.3% of the median sales price for the study period).

We found that six years was the shortest lag that showed a significant association between tree planting and neighborhood desirability. As the lag lengthened from six to twelve years, the coefficients on the number of trees planted generally increased in magnitude, although the seven- and ten-year lags were not significant. At twelve years, tree planting had more than twice the impact on neighborhood desirability than at six years. This suggests that any effect of tree planting on gentrification may take over a decade to fully manifest. In addition, the insignificance of shorter time lags suggests that tree planting is not merely a proxy for an omitted variable.

Both tree planting and existing tree cover were independently associated with increased neighborhood desirability, which suggests that tree planning is not merely a proxy for existing tree cover. These findings are also consistent with previous studies showing that trees are associated with higher sales and rental prices of single-family homes in Portland and elsewhere (Donovan and Butry, 2010, 2011; Siriwardena et al., 2016). Our findings are also consistent with previous studies showing that major green infrastructure projects may be drivers of gentrification (Immergluck and Balan, 2017; Rigolon and Németh, 2018), although the magnitude of the association we report is lower. This difference in magnitude is not surprising, given that that large green infrastructure projects have a bigger impact on a neighborhood than tree planting projects with a mean size of 28 trees. Similarly, our findings are consistent with past research showing that neighborhoods with more trees have higher median household income (Koo et al., 2019) and have a higher proportion of white residents (Jesdale et al., 2013).

Although we found that tree planting was associated with gentrification, the magnitude of the association was modest. This suggests that unless a large number of trees are planted in a neighborhood, it is unlikely that there will be a major impact on gentrification in the short-

Fig. 2. Trees planted in 2008, 2014, and 2020 in Portland, Oregon by Friends of Trees. Photo credit: Geoffrey Donovan. Photos taken July 6, 2020.

Table 5
Correlation coefficients between neighborhood desirability and four demographic measures of gentrification (1990–2010).

	Neighborhood desirability	Median household income	Non-Hispanic white (%)	Owner-occupied housing (%)	Didn't graduate high school (%)
Neighborhood desirability	1.00				
Median household income	0.47	1.00			
Non-Hispanic white (%)	0.53	0.39	1.00		
Owner-occupied housing (%)	0.33	0.28	0.62	1.00	
Didn't graduate high school (%)	−0.27	0.00	−0.37	−0.50	1.00

term. For example, our results suggest that 112 trees would need to be planted to increase median house price by 5% (after six years). However, our results also suggest that the gentrifying effects of trees may increase over time. In addition, we found that the magnitude of the association between neighborhood gentrification and tree planting was higher for yard trees compared to street trees. This may be because the trees planted in yards are larger species. This explanation is consistent with our finding that the magnitude of the association between tree planting and neighborhood desirability increases as trees age and grow. However, it is also possible that trees planted on private property have a bigger impact on gentrification. Therefore, particular care should be taken, if a tree-planting project is focused on private yards. Finally,

Table 6
Comparison of the association between neighborhood desirability and number of street trees planted versus the number of yard trees planted in Portland, Oregon from 1990 to 2019 (number of tracts = 138, number of observations = 2998). Mixed model with AR1 residual structure. Standard errors were estimated with the White-Huber estimator (for space reasons, standard errors are not shown).

	STREET TREES n = 50,725			YARD TREES = 7260		
Variable	Coefficient	95% CI	p-value	Coefficient	95% CI	*p*-value
Year (reference 1996)						
1997	6245	−625 to 13,115	0.075	6318	−580 to 13,216	0.073
1998	4922	−1651 to 11,495	0.142	5282	−1296 to 11,861	0.116
1999	3400	−2105 to 8905	0.226	3605	−1881 to 9092	0.198
2000	3964	−2818 to 10,746	0.252	4358	−2419 to 11,135	0.208
2001	2478	−3748 to 8705	0.435	3170	−3101 to 9441	0.322
2002	2799	−3722 to 9319	0.400	3484	−2994 to 9962	0.292
2003	5903	−3443 to 15,249	0.216	6881	−2383 to 16,144	0.145
2004	5711	−3254 to 14,676	0.212	6813	−2152 to 15,779	0.136
2005	8987	−2754 to 20,728	0.134	10,467	−1196 to 22,129	0.079
2006	8374	−2562 to 19,310	0.133	9995	−741 to 20,731	0.068
2007	8786	−4592 to 22,164	0.198	10,082	−3243 to 23,407	0.138
2008	4749	−5924 to 15,423	0.383	6425	−4191 to 17,042	0.236
2009	10,967	−1172 to 23,106	0.077	11,512	−672 to 23,697	0.064
2010	7834	−3160 to 18,827	0.163	8197	−2824 to 19,217	0.145
2011	18,424	3527 to 33,321	0.015	19,408	4517 to 34,298	0.011
2012	18,175	2648 to 33,702	0.022	18,861	3363 to 34,360	0.017
2013	19,722	3802 to 35,642	0.015	20,402	4560 to 36,245	0.012
2014	24,302	7046 to 41,559	0.006	24,865	7590 to 42,139	0.005
2015	24,006	7069 to 40,942	0.005	24,464	7398 to 41,529	0.005
2016	23,736	5991 to 41,481	0.009	24,455	6863 to 42,047	0.006
2017	27,641	9325 to 45,957	0.003	28,979	10,875 to 47,083	0.002
# light-rail stops (2-year lead)	5437	170 to 10,704	0.043	5395	79.9 to 10,710	0.047
NRHP (binary)	21,266	8203 to 34,328	0.001	21,766	8626 to 34,905	0.001
Tree cover (%)	881	225 to 1536	0.008	880	220 to 1540	0.009
Mean house age (years)	399	157 to 640	0.001	409	165 to 654	0.001
Mean house size (m2)	558	332 to 784	<0.001	551	165 to 654	0.001
# trees planted (6-year lag)	130	47 to 214	0.002	391	25.8 to 757	0.036
Random-effects parameters						
Tract-level random intercept variance	7.94E+08	5.58e+08 to 1.13e+09		8.24E+08	5.87e+08 to 1.16e+09	
AR(1): rho	0.513	0.424 to 0.593		0.515	0.426 to 0.595	
AR(1): within group error variance	1.95E+09	1.72e+09 to 2.21e+09		1.96E+09	1.73e+09 to 2.22e+09	

results are specific to Portland. In another city, it is possible that tree planting may have a bigger impact on gentrification. Therefore, organizations that plan to plant a large number of trees in a neighborhood may wish to partner with non-profits and government agencies that work to ameliorate the effects of gentrification.

The possible gentrifying effect of tree planting should be balanced against the benefits that trees can provide to residents of low-income and minority neighborhoods. For example, trees can absorb air pollution (Nowak et al., 2006), and studies have shown that neighborhoods with lower household income (Kristiansson et al., 2015) and a higher proportion of residents who are ethnic minorities (Perlin et al., 2001) are more likely have higher levels of air pollution. In addition, multiple studies have shown that exposure to trees can improve public-health outcomes (James et al., 2015), and a subset of these studies have found that the health benefits of exposure to nature are greatest for those with lower socioeconomic status (Agay-Shay et al., 2014; Dadvand et al., 2012). Finally, crime is a particularly important issue in low-income and minority neighborhoods, and several studies have shown that trees are associated with lower crime (Donovan and Prestemon, 2012; Kuo and Sullivan, 2001).

Given the benefits of exposure to trees, we believe it would be short sighted to refrain from tree planting in under-privileged neighborhoods for fear of gentrification, as withholding tree benefits would compound the disadvantages that residents already face. However, our results do suggest that planting trees makes a neighborhood more desirable, so organizations that undertake tree-planting programs should be mindful of possible unintended consequences. Tree planting is a cost-effective way of improving the environment of under-privileged neighborhoods. However, it would be counterproductive if such efforts displaced the residents that tree-planting programs were designed to benefit.

Our study has several limitations. This is an observational study, so we were unable to demonstrate that trees are causally associated with gentrification. We chose to use a single measure of gentrification based on sales-price data, as this allowed us to analyze gentrification longitudinally. However, it's possible that tree planting may not be associated with other gentrification metrics. Our tree-planting data did not capture all trees planted during the study period. If these missing trees are systematically correlated with our planting data, then model coefficients could be biased. Similarly, we did not account for all drivers of gentrification, and if any of these omitted variables were correlated with the number of trees planted, then model coefficients could also be biased. We only had data on tree planting, and some of these trees will have died or been removed during the study period. Conversations with Friends of Trees suggests that this loss of trees is not greater in particular neighborhoods, but we do not have any data to support this assertion. Despite these limitations, we believe that results suggest that tree planting may increase neighborhood desirability and results in gentrification.

Declaration of Competing Interest

None of the authors have any conflicts of interests.

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