Urban Forestry & Urban Greening 38 (2019) 330–336

Contents lists available at ScienceDirect

Urban Forestry & Urban Greening

journal homepage: www.elsevier.com/locate/ufug

Urban trees, house price, and redevelopment pressure in Tampa, Florida

Geoffrey H. Donovan[a,*], Shawn Landry[b], Cody Winter[c]

[a] USDA Forest Service, PNW Research Station, 620 SW Main, Suite 502, Portland, OR, 97205, USA
[b] University of South Florida, School of Geosciences, 4202 E Fowler Ave., NES107, Tampa, FL, 33620, USA
[c] Environmental Protection Commission, 3629 Queen Palm Drive, Tampa, FL, 33619, USA

ARTICLE INFO

Keywords:
Hedonic
Urban forestry
Non-market valuation
Tampa
Externality

ABSTRACT

We examined the relationship between urban trees and the sales price of single-family homes in Tampa, Florida. We chose Tampa, because the city is facing major redevelopment pressure that may impact the association between trees and house price. In particular, a frequently voiced view in Tampa's development community is that trees adversely affect the value of houses that are being sold for redevelopment. We estimated hedonic models of sales price controlling for house and neighborhood characteristics and correcting for spatial auto-correlation (n = 1,924). We found that trees within 152m (500 feet) of a house's lot were significantly associated with higher sales prices. Specifically, a 1-percentage point increase in tree-canopy cover was associated with a total increase in sales price of $9,271 to $9,836 (results were largely insensitive to correction for spatial auto-correlation). Our results demonstrate that, even in a city facing major redevelopment pressure, trees are associated with higher sales prices.

1. Introduction

Multiple studies have found that proximity to trees can increase the sales price of houses (Anderson and Cordell, 1988; Donovan and Butry, 2010; Pandit et al., 2014; Payton et al., 2008). However, the positive association between trees and house price is not universal. For example, several studies have found that trees on a house's lot are either uncorrelated with sales price or are associated with lower sales prices (Donovan and Butry, 2010; Pandit et al., 2014; Saphores and Li, 2012). Similarly, in a study in Quebec, Des Rosiers et al. (2002) found that trees on a house's lot were positively associated with sales price but only up to a threshold: on properties with high tree cover, additional trees were associated with lower sales prices. In summary, while trees are often associated with higher sales prices, context matters. One component of this context, that has received little attention in the literature, is redevelopment pressure. In cities where a greater proportion of houses are bought for redevelopment, the presence of trees on a lot, especially if a city has strong tree-protection ordinances, may increase redevelopment costs (Landry et al., 2014). These increased costs may, in turn, result in reduced sales prices. We assess this hypothesis in Tampa, a city in southwest Florida that has experienced rapid growth and continues to face considerable redevelopment pressure (City of Tampa, 2018a). Note that we define redevelopment as a new building on a lot with an existing structure (the existing structure can be removed or retained), whereas we define development as building on an empty lot.

1.1. Literature review

Early studies of trees and house price used simple statistical models and coarse tree metrics that did not account for tree-canopy cover or tree height. For example, Morales (1980) classified the tree cover around 60 houses in Manchester, Connecticut as either good or not. They defined good tree cover as a "substantial amount of mature tree cover" and bad cover as no mature trees. Houses with good tree cover sold for 6% more than comparable houses without good tree cover. Anderson and Cordell (1988) assessed the impact of front-yard trees on the sales price of 844 single-family homes in Athens Georgia. They found that houses landscaped with trees sold for 3.5%–4.5% more than comparable houses without trees. Tyrvainen (1997) examined the effect of proximity to forested parks on the sales price of 1006 apartments sold in North Carelia, Finland. She found apartments close to forested parks (of at least 0.3 ha), and those in neighborhoods with more forest cover, sold at a price premium. In the UK, Willis and Garrod (1993) examined the impact of proximity to Forest Commission land on the sales price of homes. They found that a greater area of broadleaf forest in the 1 km^2 surrounding a home was associated with higher sales prices, whereas a greater area of Sitka spruce was associated with lower

* Corresponding author.
E-mail addresses: gdonovan@fs.fed.us (G.H. Donovan), landry@usf.edu (S. Landry), winterc@epchc.org (C. Winter).

https://doi.org/10.1016/j.ufug.2019.01.014
Received 22 October 2018; Received in revised form 14 January 2019; Accepted 17 January 2019
Available online 25 January 2019
1618-8667/ Published by Elsevier GmbH.

sales prices.

More recent studies have used finer-scale tree metrics and more sophisticated regression techniques. In particular, most hedonic studies now test and correct for spatially-autoregressive processes. Sander et al. (2010) quantified the relationship between tree cover and the sales price of 9990 single-family homes that sold in Minnesota in 2005. They found that trees in 100 m and 250 m buffers around homes were associated with higher sales prices. The magnitude of this relationship was greater for trees in the 250 m buffer, suggesting that neighborhood trees—that are not on, or immediately adjacent to, a house's lot—are the most desirable. Donovan and Butry (2010) used a combination of satellite and by-hand measures of tree-canopy cover to assess the impact of street trees on the sales price of homes in Portland, Oregon. They found that a street tree is associated with an increase in sales prices of $19,958. However, only about one third of that benefit is experienced by the house a tree fronts; the rest spills over to houses within 30 m. Using satellite imagery, Saphores and Li (2012) estimated the impact of lot and neighborhood trees on the sales price of 20,660 single-family homes that sold in Los Angeles, California in 2003 and 2004. On average, they found that lot and neighborhood trees were associated with higher sales prices. However, in 40% of sales, lot trees were negatively associated with sales price. In contrast, in only 3% of sales were neighborhood trees negatively associated with sales price. Payton et al. (2008) measured greenness in 2- and 11-acre (0.8- and 4.5-ha) buffers around 9716 single-family homes that sold in Indianapolis, Indiana in 2004. They found that greenness in both buffers was associated with higher sales prices, but, consistent with other studies, greenness in the 11-acre buffer had a larger impact on sales price. Finally, Pandit et al. (2014) examined the relationship between trees and the sales price of 5606 single-family homes that sold in Perth in 2009. They found that lot trees were associated with lower sales prices, whereas neighborhood trees, on public land, were associated with higher prices. Specifically, a 10% increase in tree cover on adjacent pubic land was associated with an increase in sales price of AU $14,500.

It is not surprising that houses with trees sell at a price premium, as studies have shown that trees are associated with a wide range of benefits to homeowners including improved health outcomes (Donovan et al., 2013; Mitchell and Popham, 2008), lower crime (Kuo and Sullivan, 2001; Troy et al., 2016), better air quality (Nowak et al., 2006), and reduced energy use (Akbari et al., 1997; Donovan and Butry, 2009).

2. Methods

2.1. Data and study area

Tampa is a rapidly growing city in southwest Florida: its population has increased from 303,333 in 2000 to 385,430 in 2017 (U.S. Census, 2017). Population projections from the Florida Housing Data Clearinghouse suggest sustained growth rates through at least 2040 (2018). In addition, there is a limited amount of undeveloped land in desirable neighborhoods and close to water. In consequence, Tampa faces significant redevelopment pressure. A commonly voiced belief amongst developers in Tampa is that trees are an impediment to this redevelopment. Landry et al. (2014) interviewed multiple developers, contractors, and landscape architects in Tampa. The prevailing view was that trees can significantly increase redevelopment costs, and that these additional costs mean that houses with trees suffer a sales-price penalty. For example, one developer said that this price penalty could be "…$200,000–300,000 based on whether a lot is buildable or not depending on the trees." If developers are right, and trees do reduce the sales price of homes, then this could fundamentally change how urban trees are managed in cities that have major redevelopment pressure.

Our sample consisted of all single-family homes that sold in Tampa from May 2015 to May 2016 (n = 4848). We only considered the sales of lots with existing homes not empty lots sold for new development. We chose this sample frame, because the urban tree-canopy cover (UTC) dataset used for the study (Landry et al., 2018) was based on aerial imagery taken between December 1, 2015 and January, 18 2016. Data on sales prices and house characteristics were obtained from the Hillsborough County Property Appraisers Office (HCPA; https://www.hcpafl.org). In our regression models, we used a randomly-selected subsample (n = 1924), because we did not have time to do manual measures (described below) of tree-canopy cover for all 4848 houses. Table 1 provides summary statistics for select variables from the analytical sample, and Fig. 1 shows the location of houses in the analytical sample, neighborhood boundaries, and tree-canopy cover.

Table 1
Descriptive statistics for house sales price and independent variables.

Variable	Mean	Median	SD	Minimum	Maximum
Sales Price ($)	282,524	198,000	306,429	8,500	4,249,998
Bedrooms	3.14	3	0.989	0	7
Bathrooms	2.12	2	0.976	1	7
Number of stories	1.22	1	0.454	1	4
Lot size (m2)	779	689	462	202	5,666
Finished area (m2)	183	182	3	37	949
Water front (%)	2.3	–	–	–	–
Flood zone (%)	16.8	–	–	–	–
Garage (%)	49.2	–	–	–	–
Carport (%)	21.7	–	–	–	–
Porch (%)	62.5	–	–	–	–
Pool (%)	15.1	–	–	–	–
Percent tree cover on lot	45.8	45.5	25.2	0	100
Percent tree cover within 100 ft (30.5 m)	43.2	43.8	17.5	0	100
Percent tree cover within 500 ft (152 m)	41.5	41.8	19.2	0	100

We created a list of candidate variables describing house characteristics based on the hedonic literature and conversations with the (then) HPCA, Director of Valuation (Wilmath, 2016). We accounted for differences in neighborhood characteristics (school district, for example) by using the neighborhood code assigned to each parcel by the HCPA. The neighborhood code was created by the HCPA, following the guidelines of the International Association of Assessing Officers which defines a neighborhood based on "…natural, man-made or political boundaries and is established by a commonality based on land use, types and age buildings or population, the desire for homogeneity, or similar factors" (Eckert et al., 1990). There were 98 neighborhoods in our analytical sample.

Tree-canopy cover data were provided by Landry et al. (2018) as part of a UTC dataset for the entire City of Tampa. Tree-canopy cover was mapped as part of a land-cover classification that used object-based image analysis (O'Neil-Dunne et al., 2014). The tree-canopy cover map (defined as tree canopy from trees that were greater than 2.5 m tall) was based on six-inch resolution, multi-spectral (blue, green, red, near-infrared) aerial imagery from early spring 2016 (collected December 1, 2015 and January 18, 2016), as well as ancillary spatial data (road centerlines, water or wetland boundaries, and building footprints, for example). Extensive manual corrections were then made, and a visual accuracy assessment of 4199 randomly distributed points indicated an overall accuracy of 92.2%. Tree-canopy cover, and all spatial data, were converted to a State Plane (NAD83, Florida West) projected coordinate system, and planar distances were used for all measurements.

Several previous studies have found that trees on a house's lot may be less valuable than trees in a house's immediate neighborhood. Unfortunately, distinguishing between lot and neighborhood trees with remotely-sensed data is difficult, as it's often not possible to locate a tree's stem on aerial imagery using an automated process. In addition, using canopy cover that falls on a house's lot as a metric of tree cover is problematic, because the ownership of the tree—along with maintenance costs and legal responsibilities—depend on the location of the

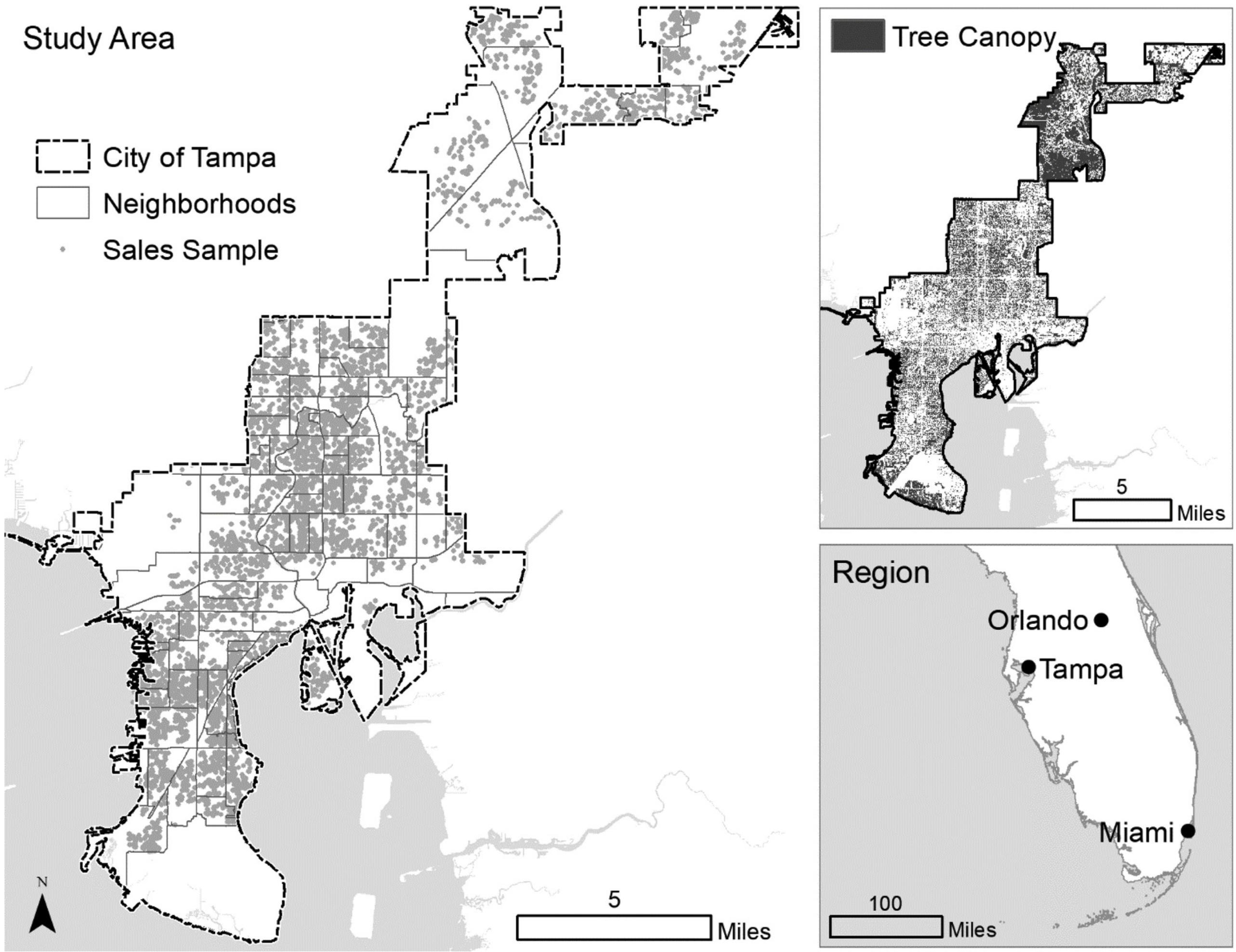

Fig. 1. Location of house sales in the analytical sample, neighborhood boundaries, and tree-canopy cover.

tree's stem not the location of the canopy. This may be particularly relevant in this study, as we are investigating whether the presence of a tree on a house's lot may negatively impact sales price. Therefore, we augmented remotely-sensed data with by-hand measurements to more accurately determine how much tree-canopy cover a homeowner was legally responsible for, even if this canopy overhung neighboring properties. This allowed us to distinguish between lot trees, that a homeowner is legally responsible for, and neighborhood trees that a homeowner is not legally responsible for.

Referencing parcel boundaries and the same aerial imagery used for tree-canopy cover mapping, we used a geographic information system (ArcGIS 10.3; ESRI Corporation) to trace a polygon around all tree-canopy cover that originated within each of the 1924 parcels sampled from the original 4848 houses (see Fig. 2). In other words, each polygon delineated the extent of tree-canopy cover (from the UTC dataset) for trees originating on a single parcel. A zonal tabulation then used these polygons to quantify the percentage of tree-canopy cover associated with each parcel. In addition, based on previous research which found an influence on property value from surrounding trees (Donovan and Butry, 2010), we calculated the percentage of tree-canopy cover within a 30.5 m (100 feet) buffer (0.29 ha/0.72 acre area) surrounding each parcel; and the percentage of tree-canopy cover within a 152 m (500 feet) buffer (7.2 ha / 18 acre area) surrounding each parcel. Buffer sizes were chosen to represent the influence of adjacent parcels (30.5 m) and a larger neighborhood area (152 m).

2.2. Statistical analysis

We estimated the relationship between the sales price of homes and tree-canopy cover using the hedonic method, which is a statistical model that has been used for decades to estimate the impact of environmental amenities and disamenities on the sales prices of houses (Rosen, 1974). Sales price is regressed against house and neighborhood characteristics as well as the environmental amenity under study. The environmental-economics literature does not provide any definitive guidance on the appropriate functional form for hedonic models (Taylor, 2003), so we estimated several models with different logarithmic, semi-logarithmic, and Box-Cox specifications. We chose between them using residual plots and goodness-of-fit statistics.

Spatial autocorrelation is a common statistical issue that arises when estimating hedonic models. The spatial autocorrelation can take several forms. In a spatial-lag process, the sales price of homes are spatially correlated; in a spatial-error process, the residuals of the hedonic model are spatially correlated; in a joint lag-and-error process, both sales prices and model residuals are spatially correlated. Failing to correct for these spatially autoregressive processes can results in estimates of regression coefficients that are inefficient or biased (Anselin and Bera, 1998).

We investigated the presence of spatial autocorrelation using a semivariogram of residuals from an ordinary least squares (OLS) hedonic model. A semivariogram graphically displays the results of pairwise comparisons made between observations (residuals in our case) over space. When spatial autocorrelation is present, the difference

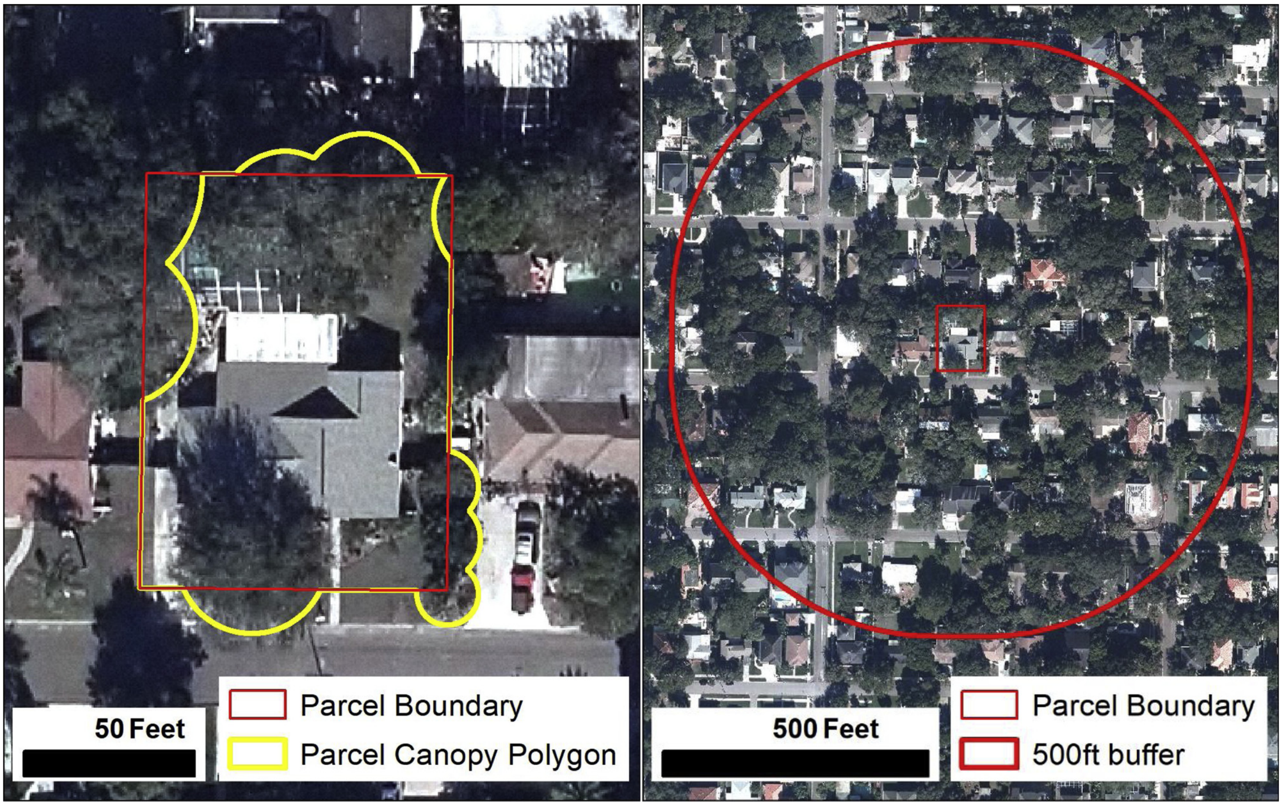

Fig. 2. Example polygon delineating tree-canopy cover originating on a single lot (left) and area of 500 foot distance from the same lot (right). Trees within the yellow boundary are lot trees (for which the homeowner is legally responsible), whereas trees outside the yellow boundary are neighborhood trees (for which the homeowner is not legally responsible) (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

between observations is smaller for pairs that are closer together. We chose to evaluate spatial autocorrelation with a semivariogram, because doing so didn't require any assumptions about the form of any spatial relationships. In contrast, statistical tests of spatial autocorrelation—the Lagrangian Multiplier test, for example—require the analyst to specify the form of the hypothesized spatial relationship (Anselin and Hudak, 1992). A semivariogram also provides information—the spatial range of the autocorrelation, for example—that helps correctly specify the form and extent of any spatial relationship in subsequent regression models (Donovan et al., 2007). However, a semivariogram cannot distinguish between spatial lag and error processes. Therefore, we estimated a spatial lag (Eq. (1)), a spatial error (Eq. (2)), and a joint lag-and-error hedonic model:

$$P = \rho \boldsymbol{W} P + \boldsymbol{\beta X} + \mu \tag{1}$$

$$P = \boldsymbol{\beta X} + \lambda \boldsymbol{W} \varepsilon + \mu \tag{2}$$

Where P denotes the sales price of homes; $\boldsymbol{X}$ is a vector of independent variables; $\boldsymbol{\beta}$ is a vector of coefficients that is estimated in the regression step; $\boldsymbol{W}$ is an n by n spatial-weights matrix that specifies the spatial relationship between either sales prices or residuals; ρ (rho) and λ (lambda) are spatial coefficients that are estimated in the regression step; μ and ε are independent and identically distributed error terms. In the joint lag-and-error model, both sales price and the error term are spatially autoregressive (equation not shown). Theoretically, the two spatial-weights matrices in the joint model could be different. However, in practice there is seldom empirical justification for using different matrices (Anselin, 2003). The elements of a spatial-weights matrix define the spatial relationship between pairs of observations. Two of the most commonly used spatial patterns are inverse distance and inverse distance squared (Elhorst, 2003). In both cases, the strength of the spatially autoregressive process declines as the distance between two observations increases. This decline is steeper when using an inverse-distance squared matrix. We estimated lag, error, and lag-and-error models using both inverse-distance and inverse-distance squared matrices, and we chose between the two using the Akaike Information Criterion (AIC).

In addition to these three spatial models, we estimated a non-spatial mixed regression model that included neighborhood-level random effects (in the spatial models, indicator variables for neighborhood were included as part of the fixed component of the models).

We employed a two-stage model-selection process. First, we used backwards selection with progressively lower p-value thresholds (final threshold $p < 0.05$) to estimate a hedonic model without variables describing trees. Second, we added tree variables to this base model again using backwards selection. To avoid including highly collinear combinations of variables in our models, we estimated OLS versions of each model (without neighborhood-level random effects or any correction for spatial autocorrelation), which allowed us to calculate variance-inflation factors for each independent variable (we dropped any variable with a VIF > 10). To investigate the presence of heteroscedasticity, we used residual plots.

3. Results

We found that a semi-log functional form had the best fit in all four models: the dependent variable is the natural log of sales price and all variables enter linearly. Our semivariogram analysis revealed a clear spatial pattern in the residuals from an OLS model (Fig. 3). We found that correcting for this spatial autocorrelation using an inverse-distance, rather than inverse-distance squared, spatial-weights matrix gave lower AIC values for all spatial models (Table 2). Finally, none of the independent variables included in our models had a variance-inflation factor over ten, and residual plots did not show any evidence of heteroscedasticity.

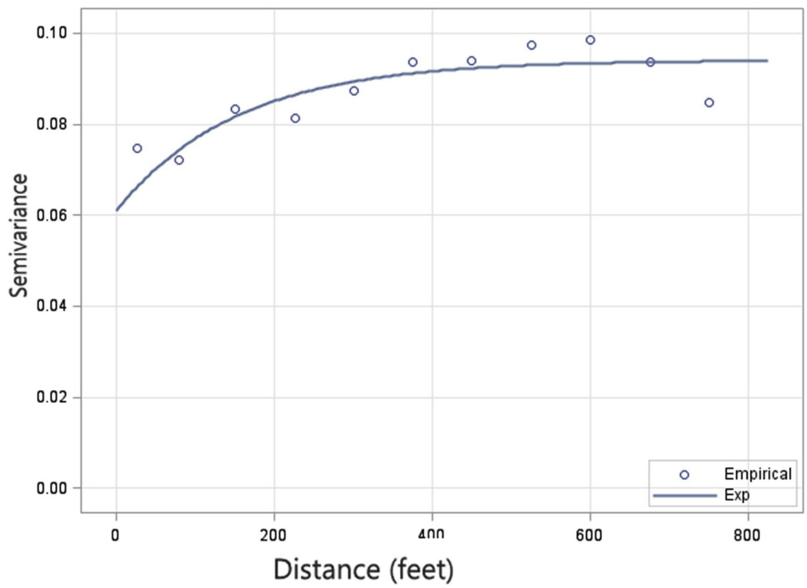

Fig. 3. Semivariogram of residuals from an ordinary least squares regression model of house sales price against house and neighborhood characteristics in Tampa, Florida (n = 1924). Circles denote the semivariance from the model residuals (empirical), while the solid line is an exponential trend line.

The sign of the coefficients on housing and neighborhood characteristics conformed to *a priori* expectations (Table 2). In addition, coefficients varied only modestly across the four different models, which suggests that results are not sensitive to correction for spatial autocorrelation nor the form this correction takes. Note that we included 90 indicator variables for neighborhood in the three spatial models, but for clarity we have not included the results in Table 2 (full results available from the authors). Although there are 98 neighborhoods in Tampa, only 91 contained a sale from our sample.

Neither tree cover on a house's lot, nor tree cover within 30.5 m (100 feet) of a house, were significantly associated with sales price. However, tree cover within 152 m (500 feet) of a house was significant. In addition, the coefficient for tree cover within 152 m of house was consistent across the four models: 0.0936 (mixed model) to 0.0993 (lag-and-error model). Interpreting the magnitude of this coefficient is complicated by the model's semi-log form. Therefore, we back transformed the tree coefficient at the median of sales price (back transformation at sales prices other than the median is problematic). Based on the median house price of $165,000, a 1-percentage point increase in tree-canopy cover within 152 m of a house was associated with a $155 to $164 increase in sales price (depending on the model formulation). In our sample, there were 60 homes on average within 152 m of a house. Therefore, a 1-percentage point increase in tree-canopy cover is associated with a total increase in sales price of $9271 to $9836.

We can also express these results in terms of an average tree. Using tree crowns measurements from 69 field plots (0.04 ha size) on residential land in Tampa (Landry et al., 2013), we found that the average canopy size for a tree on the lot of a single-family home was 108 square meters (1167 square feet). This corresponds to an increase in sales price to homes in the neighborhood of $1378–$1461 attributable to the average tree on a single-family property.

4. Discussion

Tampa is a rapidly growing city in Southern Florida that is facing strong redevelopment pressure. A widely held view in the Tampa development community is that trees are an impediment to this redevelopment, and that properties with more trees sell at a discount compared to equivalent properties without trees. We found no evidence to support this view: trees on a house's lot were not significantly associated with sales price. This result is consistent with other studies that found either no relationship between lot trees and sales price or found that lot trees were negatively associated with sales price (Donovan and Butry, 2010; Pandit et al., 2014; Saphores and Li, 2012). We did, however, find that trees within 152 m (500 feet) of a house were significantly and positively associated with sales price. Again, this result is consistent with previous studies that found that houses with trees close to, but not on, the lot sold at a price premium (Donovan and Butry, 2010; Pandit et al., 2014; Payton et al., 2008; Sander et al., 2010; Saphores and Li, 2012). Our results do not provide any support for the assertion that trees can reduce the sales price of homes in Tampa, nor do results support changing urban-tree polices and regulations in areas facing redevelopment pressure.

Our failure to find a sales-price penalty associated with lot trees may be, in part, an artifact of our sample. Results may have been different, if we had been able to restrict the sample to solely houses sold for redevelopment, but we were unable to do so; therefore, we included all sales in our analysis. However, if trees do impose a redevelopment price penalty, then one would expect this price penalty to also impact houses that aren't sold for redevelopment. For example, trees may dissuade a developer from making an offer on a house, and economic theory suggests that reducing the number of parties interested in a sale would negatively affect the sales price of a home, even if that home is bought by someone who isn't interested in redevelopment.

The magnitude and spatial extent of the observed tree price premium has policy implications. In particular, we found that the sales price of a home may be affected by trees on neighboring properties. This is a classic example of a positive externality in which a person bears all the costs of a transaction (buying and maintaining a tree, in this case) but does not receive all the benefits. Absent corrective action, the positive externality we identified will result in an underinvestment in trees from a societal perspective. A number of policy remedies are available. A city can place restrictions on the removal of trees on private land; a subsidy for tree planting could be offered; a city could assume responsibility for the planting and maintenance of street trees. In many cities, the provision and maintenance of street trees is the responsibility of the adjacent property owner despite the trees being on public land. In Tampa, the city has had strict tree-protection regulations for over four decades (Landry et al., 2010, 2014) and provide a free tree-planting program for home owners (CIty of Tampa, 2018b).

Our results were largely insensitive to correction for spatial

Table 2
Regression results for mixed, spatial error, spatial lag, and lag-and-error models of the natural log of sales price (n = 1924). For clarity, the coefficients on neighborhood-level fixed effects in the lag-and-error, error, and lag models are not reported (results available from the authors).

VARIABLES	*ERROR* Coefficient	*LAG* Coefficient	*LAG AND ERROR* Coefficient	*MIXED* Coefficient
Bedrooms	0.0541***	0.0540***	0.0523***	0.0492***
Bathrooms	0.0569***	0.0584***	0.0587***	0.0616***
Heated area of house (ft^2)	0.000282***	0.000277***	0.000275***	0.000291***
Stories	−0.0657**	−0.0622*	−0.0616*	−0.0627*
Area of lot (acres)	0.440***	0.440***	0.444***	0.420***
Year built	0.00674***	0.00671***	0.00671***	0.00647***
Garage	0.143***	0.140***	0.142***	0.150***
Carport	0.0624***	0.0615***	0.0632***	0.0659***
Front porch (> 50 ft^2)	0.0659***	0.0643***	0.0638***	0.0681***
Pool	0.0892***	0.0867***	0.0873***	0.0933***
Water front	0.438***	0.446***	0.447***	0.422***
Tree cover within 152 m (500 feet) of house	0.0965**	0.0962**	0.0993**	0.0936*
ARCHITECTURE (Omitted: basic 1 story)				
Basic Multi-Story	−0.0048	−0.00925	−0.0079	−0.0156
Contemporary 1-Story	0.00419	0.0059	0.0114	0.00936
Contemporary Multi-Story	−0.0732	−0.0812*	−0.0769	−0.0708
Mansion	−1.406***	−1.402***	−1.382***	−1.478***
Pre-1940 1-Story	0.0985***	0.0919**	0.0930**	0.0928**
Pre-1940 Multi-Story	0.279***	0.269***	0.276***	0.279***
Unique Design	−0.528	−0.503	−0.512	−0.514
Updated Basic 1-Story	0.215***	0.212***	0.213***	0.216***
Updated Basic Multi-Story	0.176**	0.169**	0.170**	0.182**
Updated Contemporary 1-Story	0.298**	0.284**	0.274**	0.300**
Updated Contemporary Multi-Story	0.0332	0.0391	0.0557	0.044
Updated Pre-1940 1-Story	0.539***	0.526***	0.531***	0.532***
Updated Pre-1940 Multi-Story	0.667***	0.660***	0.668***	0.661***
Updated Unique Design	0.33	0.313	0.318	0.326
AC Type (Omitted: central)				
Non-ducted	−0.267***	−0.266***	−0.267***	−0.282***
No AC	−0.629***	−0.623***	−0.626***	−0.628***
Roof type (omitted: Asbestos)				
Asphalt/Comp. Shingle	0.309*	0.321*	0.310*	0.312*
Built up Tar & Gravel	0.377**	0.378**	0.369**	0.370**
Metal	0.372**	0.384**	0.373**	0.371**
Minimum	0.306*	0.329*	0.311*	0.306
Rolled Composition	0.324*	0.326*	0.314*	0.327*
Rubber or Plastic	0.382*	0.398*	0.382*	0.385*
Slate	0.574	0.593	0.572	0.599
Tile	0.279	0.292*	0.284	0.283
AIC (inverse-distance)	958.5	947.7	944.3	
AIC (inverse-distance squared)	959.3	954.2	953.6	
lambda	−1.812***		−0.730**	
rho		0.448***	0.504***	

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

autocorrelation. In particular, it is encouraging that results weren't sensitive to assumptions about the form of the autocorrelation (lag *versus* error process, for example).

Our study has a number of limitations. It is an observational, so we weren't able to show a causative relationship between trees and sales price. In addition, we weren't able to restrict the sample to houses sold specifically for redevelopment. Results may have been different had we been able to do so. Finally, our tree metrics were two dimensional; they did not capture tree height or crown volume. Nonetheless, we believe that our results support previous research demonstrating that trees can increase the sales price of houses and we further demonstrate that this relationship holds in a city like Tampa that faces major redevelopment pressure.

Acknowledgements

We thank the City of Tampa for their financial support of the City of Tampa Tree Canopy and Urban Forest Analysis study, which provided the tree canopy cover data. We also thank Kathy Beck and Catherine Coyle for their guidance and knowledge regarding Tampa policies and development trends, as well as Tim Wilmath for provide advice regarding the Property Appraiser data. We also thank the collaborators of the Tampa Tree Canopy and Urban Forest Analysis, including: Dr. Michael Andreu, Robert Northrop, Andrew Koeser, Drew McLean, Deb Hilbert and Jarlath O'Niel-Dunne.

References

Akbari, H., Kurn, D.M., Bretz, S.E., Hanford, J.W., 1997. Peak power and cooling energy savings of shade trees. Energy Build. 25, 139–148.
Anderson, L., Cordell, H.K., 1988. Influence of trees on residential property values in Athens Georgia (U.S.A.): a survey based on actual sales prices. Landsc. Urban Plan. 15, 153–164.
Anselin, L., 2003. Spatial externalities, spatial multipliers, and spatial econometrics. Int. Reg. Sci. Rev. 26, 153–166.
Anselin, L., Bera, A., 1998. Saptial dependence in linear regression models with an introduction to spatial econometrics. In: Ullah, A., Giles, D. (Eds.), Handbook of Applied Economic Statistics. Marcel Dekker, New York, NY, pp. 237–289.
Anselin, L., Hudak, S., 1992. Spatial econometrics in practice. Reg. Sci. Urban Econ. 22, 509–536.
City of Tampa, 2018a. Residential Permits Issued.
CIty of Tampa, 2018b. Tree-Mendous Tampa, Tampa, Florida.
Des Rosiers, F., Theriault, M., Kestens, Y., Villeneuve, P., 2002. Landscaping and house values: an empricial investigation. J. Real Estate Res. 23, 139–161.
Donovan, G.H., Butry, D.T., 2009. The value of shade: estimating the effect of urban trees on summertime electricity use. Energy Build. 41, 662–668.

Donovan, G.H., Butry, D.T., 2010. Trees in the city: valuing street trees in Portland, Oregon. Landsc. Urban Plan. 94, 77–83.
Donovan, G.H., Champ, P.A., Butry, D.T., 2007. The impact of wildfire risk on housing price: a case study from Colorado Springs. Land Econ. 83, 217–233.
Donovan, G.H., Butry, D.T., Michael, Y.L., Prestemon, J.P., Liebhold, A.M., Gatziolis, D., Mao, M.Y., 2013. The relationship between trees and human health: evidence from the spread of the emerald ash borer. Am. J. Prev. Med. 44, 139–145.
Eckert, J.K., Gloudemans, R.J., Almy, R.R., 1990. Property Appraisal and Assessment Administration Int. Assn. Assess. Off.
Elhorst, J.P., 2003. Specification and Estimation of Spatial Panel Data Models. Int. Reg. Sci. Rev. 26, 244–268.
Florida Housing Data Clearing House, 2018. Population by age projections. Perman. Resid. 2010–2040.
Kuo, F.E., Sullivan, W.C., 2001. Environment and crime in the inner city: does vegetation reduce crime? Environ. Behav. 33, 343–367.
Landry, S., Pu, R.J.L., Planning, U., 2010. The impact of land development regulation on residential tree cover: an empirical evaluation using high-resolution IKONOS imagery. Landsc. Urban Plan. 94, 94–104.
Landry, S., Northrop, R., Andreu, M., Rhodes, C.C., Tampa, 2013. Urban Forest Analysis: the Structure Composition Function and Economic Benefits of Trees and the Urban Forest. City of Tampa 2011, FL, USA.
Landry, S.M., Northrop, R.J., Andreu, M.G., Beck, K., 2014. City of Tampa urban forest management, monitoring and policy. Geogr. 45, 44–62.
Landry, S., Koeser, A., Northrop, R., McLean, D., Donovan, G.H., Andreu, M., Hilbert, D., 2018. City of Tampa Tree Canopy and Urban Forest Analysis 2016. City of Tampa, Tampa, Florida.
Mitchell, R., Popham, F., 2008. Effects of exposure to natural environment on health inequalities: an observational population study. Lancet 372, 1655–1660.
Morales, D.J., 1980. The contribution of trees to residential property value. J. Arboricult. 6, 305–308.
Nowak, D.J., Crane, D.E., Stevens, J.C., 2006. Air pollution removal by urban trees and shrubs in the United States. Urban For. Urban Green. 4, 115–123.
O'Neil-Dunne, J., MacFaden, S., Royar, A.J.R.S., 2014. A versatile, production-oriented approach to high-resolution tree-canopy mapping in urban and suburban landscapes using GEOBIA and data fusion. Remote Sens. 6, 12837–12865.
Pandit, R., Polyakov, M., Sadler, R., 2014. Valuing public and private urban tree canopy cover. Aust. J. Agric. Resour. Econ. 58 (3), 453–470.
Payton, S., Lindsey, G., Wilson, J., Ottensmann, J.R., Man, J., 2008. Valuing the benefits of the urban forest: a spatial hedonic approach. J. Environ. Plan. Manag. 51, 717–736.
Rosen, S., 1974. Hedonic prices and implicit markets: product differentiation in pure competition. J. Polit. Econ. 82, 34–55.
Sander, H., Polasky, S., Haight, R.G., 2010. The value of urban tree cover: a hedonic property price model in Ramsey and Dakota Counties, Minnesota, USA. Ecol. Econom. 69, 1646–1656.
Saphores, J.-D., Li, W., 2012. Estimating the value of urban green areas: a hedonic pricing analysis of the single family housing market in Los Angeles, CA. Landsc. Urban Plan. 104, 373–387.
Taylor, L.O., 2003. The hedonic method. In: Champ, P.A., Boyle, K.J., Brown, T.C. (Eds.), A Primer on Nonmarket Valuation, pp. 331–393 Kluwer, AA Dordrecht, The Netherlands.
Troy, A., Nunery, A., Grove, J.M., 2016. The relationship between residential yard management and neighborhood crime: an analysis from Baltimore City and County. Landsc. Urban Plan. 147, 78–87.
Tyrvainen, L., 1997. The amenity value of the urban forest: an application of the hedonic pricing method. Landsc. Urban Plan. 37, 211–222.
U.S. Census, 2017. Quick Facts: Tampa City Tampa City, Florida.
Willis, K., Garrod, G., 1993. The contribution of trees and woodland to the value of property. Arboric. J. 17, 211–219.
Wilmath, T., 2016. In: Landry, S. (Ed.), House and Neighborhood Characteristics in Hillsborough County, Florida.