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Tree cover and property values in the United States: A national meta-analysis

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ABSTRACT

Our meta-analysis uses 21 hedonic property value studies and 157 unique observations to study the influence of tree cover on the value of homes in the United States. We construct elasticity estimates of the percentage change in home value for a 1% change in the percentage of tree cover around a home. Cluster weighted averages of the elasticities account for the housing market and the precision of the property price effects for tree cover on and off property and for three categories of tree cover density. Meta-regression models further control for the housing market and tree cover heterogeneity, the methodological techniques of the primary study, and publication bias. The Mundlak meta-regression model with controls for US regions has the lowest out-of-sample transfer error. The larger elasticity for off property tree cover than on property tree cover (unless tree density is 10% or lower) suggests that the property value of homes rises more if tree cover is not on land that homeowners are responsible for maintaining. The elasticity in neighborhoods with greater than 25% tree cover (0.013) is four times larger than the elasticity in neighborhoods with 0 to 10% tree cover (0.003).

1. Introduction

Urban forests provide ecosystem services to residents that include pollutant filtering, mitigation of the heat island effect, reduction of rainwater runoff, shading, aesthetics, provision of wildlife habitat, and carbon storage (see Pataki et al., 2021 for review). A common way to estimate homeowners' willingness to pay for the services associated with neighborhood tree cover is the hedonic property value method (e.g., Sander et al., 2010). This approach assumes that a property and its location comprise a bundle of characteristics, including nearby trees. Analysts can use the method to estimate how much each characteristic contributes to the overall price of a property and how much the property price changes with small changes in tree cover.[1] Studies in over 20 communities throughout the U.S. have verified that increasing tree cover influences the property values of nearby homes (Siriwardena et al., 2016). The results of these hedonic studies are important because cities cite increases in property values as one of many benefits of programs for urban and community forest management. For example, the Chicago Region Tree Initiative, a partnership of approximately 200 organizations, is working to ensure that trees are healthier, more abundant, more diverse, and more equitably distributed to provide needed benefits, including increased property value, to all people and communities that live in the Chicago region (Chicago Region Tree Initiative, 2018). Unfortunately, not every community has the data or the funds to conduct a primary hedonic property value study to determine the effects of changing tree cover. A benefit transfer tool, based on the existing valuation studies, would allow the transfer of estimates of the values of tree canopy from cities where primary hedonic studies have been completed to cities or regions without such studies. The construction of a benefits transfer tool would help communities estimate the benefits of forest management activities that increase tree canopy or prevent the loss of tree canopy.

The analysis of multiple valuation studies from different locations (i.e. meta-analysis) for application to a new site or region is called benefit transfer, which has garnered a great deal of attention among academic economists and practitioners (Nelson and Kennedy, 2009; Newbold et al., 2018). Meta-analyses of studies using the hedonic property value method include applications to water quality (Guignet et al., 2018), air

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[1] Tree cover is a better metric than number of trees since large trees likely generate greater value than small ones.

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quality (Smith and Huang, 1995), open space (Mazzotta et al., 2014), and contaminated sites (Kiel and Williams, 2007). There is a strong consensus among practitioners that benefit transfer ought to utilize multiple estimates rather than point estimates of marginal value in order to transfer information from the study context to the policy context. Simply taking a point estimate of the value of a change in an ecosystem service from one study site for use in another ignores important differences in the socioeconomic context and can introduce substantial error into valuation and decision-making. Further, unweighted averaging over multiple point estimates from different study sites (e.g., McPherson et al., 2017) lowers the precision of the meta-analytic estimates (Nelson and Kennedy, 2009).

We systematically collate the hedonic property value literature that evaluates the effect of the percentage tree cover on home values. Most studies provide multiple observations for the meta-dataset due to several model specifications and study areas, and the number of unique observations in our dataset is 157. The primary study coefficients are converted into elasticity estimates for on property and off property tree cover and for three categories of tree cover density - low density (0–10%), medium density (10–25%), and high density (25%+). Function benefit transfer accounts for differences in the proximity-density of tree cover, publication bias, housing markets, and the statistical methodologies within and across studies. The meta-regression models we estimate for function transfer include weighted least squares and the Mundlak model suggested by Boyle and Wooldridge (2018). We evaluate the performance of the meta-regression models by comparing the out-of-sample transfer error, and the lowest transfer error occurs in the Mundlak model with US region dummies.

Our analysis highlights the importance of considering whether tree cover is on property or off property in conjunction with the tree cover density in the neighborhood. Off property tree cover has a larger effect on home value than on property tree cover, but this is only the case for the medium or high density tree cover categories. This result suggests that tree cover is a public good in the sense that increasing tree cover in a portion of a neighborhood increases home values throughout the neighborhood. Capturing this important relationship in a benefit transfer tool would help municipalities quantify the benefits of urban and community forestry programs that enhance tree cover. Further understanding of how the ecosystem services of trees influence property value requires the literature to expand to include primary studies that use tree metrics other than the percentage of tree cover. Other gaps in the literature include the lack of specificity in the type of trees, the regions covered, and the limited number of neighborhoods with tree cover greater than 40%.

The second section describes how we identify studies, generate comparable elasticity estimates, and present the summary statistics for the meta-dataset. The third and fourth sections describe the methods and results, respectively, for the calculation of the mean elasticities, publication bias, meta-regression models, and the out-of-sample transfer errors. A discussion and conclusion highlight the main results, acknowledge the limitations of the literature and benefit transfer methods, and suggest other avenues for research.

2. Meta-dataset

This section is about the construction of the meta-dataset for tree cover impacts on house prices. We indicate how we identified primary studies and chose them for the inclusion in the meta-dataset. Next, we describe the steps to make consistent elasticities for measuring the percent change in house value for a percent change in the tree cover (measured as a percentage of surface area covered by tree canopy) around a home. The elasticity computations account for the different functional forms of the hedonic regression, the amount of tree cover, and the proximity of the tree cover around the residence. Lastly, summary statistics of the meta-dataset describe the tree canopy and housing market variables and the methodological variables for the meta-regression models.

2.1. Candidate studies and inclusion criteria

A search of studies using the keywords (e.g. urban forest, property, house, and hedonic) on the relationship between property values and trees identified 47 studies. The search involved an initial review of reports, literature reviews, and meta-analyses followed by a search of several databases (e.g., Google Scholar, Treesearch, AgEcon Search, Social Science Research Network (SSRN), among others). Requests were also submitted to the RESECON Listserv for the Land and Resource Economics Network on August 7th and August 14th 2020. Our focus on the development of a credible benefit transfer tool led us to 21 primary studies that examined trees in the US with an objective tree cover measure. We dropped 26 candidate studies because those studies did not use a tree cover measure,[2] were in the grey literature and later replaced by a peer-reviewed publication within the meta-dataset, or the study area was outside the US.

Our final list of 21 studies in the meta-dataset (Table 1) has six more studies than in the Siriwardena et al. (2016) meta-analysis and literature review on property values and tree cover, providing assurance that our identified set of studies is complete. Seventeen studies are from peer-reviewed journals while the remaining four are from white papers or graduate student theses. All of the studies used sales of residential or single-family homes. The year of publication ranged from 2002 to 2019. The 21 studies provide 157 observations for the meta-dataset. There is a range in the number of observations each study provides from one observation from a single study to twenty observations from one primary study.

2.2. Comparable elasticity estimates

Nelson and Kennedy (2009) stress in the construction of a meta-dataset that there is a comparable outcome of interest across studies. All the studies use the same methodology, the hedonic property price method, so in all cases we examine how tree cover affects residential property values. The use of alternative functional forms (e.g. log-linear, double-log, linear, log-quadratic) across studies though can lead to different interpretations, and the coefficients associated with tree cover in each primary study are converted to an elasticity estimate through steps specific to each functional form. An elasticity is more appealing than a semi-elasticity because of the greater comparability of the property value response to tree cover regardless of the existing percentage of tree cover in the neighborhood. Seventeen studies use the log-linear form:

$$ln(p) = \theta X + \beta TC \tag{1}$$

where p is the real sale price, X is a vector of all variables other than tree cover, θ is the vector of coefficients on X, TC is the tree cover variable of interest, and β is the coefficient on TC. Rearranging for $p$yields $p = \exp(\theta X + \beta TC)$ and the derivative with respect to TC results in $\frac{\partial p}{\partial TC} = exp(\theta X + \beta TC)\beta = p\beta$. The formula for the elasticity equation is

$$\frac{\partial p}{\partial TC}\frac{TC}{p} = \beta TC \tag{2}$$

The sample mean for TC is plugged into Eq. (2) to generate the elasticity. Based on similar derivations, the log-quadratic form, $\ln(p) =$

[2] Alternative tree measures found in studies included the normalized difference vegetation index or the distance from the home to the nearest forest. Studies with these tree metrics were not represented in sufficient number to support separate meta-analyses.

Table 1
Summary of hedonic property value studies used in the meta-analysis.

Publication (Publication Year)	Obs.	Unit	Model	Average tree cover	Average selling price	Unweighted Mean elasticity
Cho et al. (2011)ˆ	1	Area (ac)	$ln(p) = \theta X + \beta ln(TC)$	24%	264,795	−0.001
Dimke (2008)ˆ	6	Percentage	$p = \theta X + \beta TC$	26%	276,401	0.106
Donovan et al. (2019)	4	Percentage	$ln(p) = \theta X + \beta TC$	42%	346,954	0.025
Drake-McGaughlin and Netusil (2010)ˆ	12	Percentage	$ln(p) = \theta X + \beta_1 TC + \beta_2 TC^2$	25%	373,078	0.049
Dudley (2012)	8	Area (ft^2)	$ln(p) = \theta X + \beta TC$	17%	464,540	0.001
Holmes et al. (2006)ˆ	16	Percentage	$ln(p) = \theta X + \beta TC$	8%	694,465	0.016
Holmes et al. (2010)ˆ	10	Percentage	$ln(p) = \theta X + \beta TC$	13%	322,996	0.002
Hugget (2003)ˆ	6	Percentage	$ln(p) = \theta X + \beta TC$	9%	319,633	−0.004
Kadish and Netusil (2012)	16	Percentage	$ln(p) = \theta X + \beta_1 TC + \beta_2 TC^2$	26%	392,260	0.040
Kim and Wells (2005)ˆ	2	Area (m^2)	$p = \theta X + \beta TC$	16%	417,301	−0.002
Li et al. (2019)	1	Percentage	$ln(p) = \theta X + \beta TC$	27%	147,180	0.386
Mansfield et al. (2005)ˆ	4	Percentage	$p = \theta X + \beta TC$	30%	339,418	0.018
Mei et al. (2017)	20	Percentage	$ln(p) = \theta X + \beta TC$	6%	749,452	0.050
Netusil et al. (2010)ˆ	6	Percentage	$ln(p) = \theta X + \beta_1 TC + \beta_2 TC^2$	13%	371,480	0.077
	6	Percentage	$ln(p) = \theta X + \beta ln(TC)$	14%	371,480	−0.016
Paterson and Boyle (2002)ˆ	3	Percentage	$ln(p) = \theta X + \beta TC$	61%	520,372	0.053
Price et al. (2010)ˆ	3	Percentage	$ln(p) = \theta X + \beta TC$	37%	530,710	0.026
Sander et al. (2010)ˆ	6	Percentage	$ln(p) = \theta X + \beta TC$	15%	372,080	0.002
	6	Percentage	$ln(p) = \theta X + \beta_1 TC + \beta_2 TC^2$	15%	372,080	0.002
Sander and Haight (2012)ˆ	6	Percentage	$ln(p) = \theta X + \beta TC$	14%	412,747	0.004
Saphores and Li (2012)	2	Percentage	$ln(p) = \theta X + \beta_1 TC + \beta_2 TC^2$	26%	778,038	0.002
	2	Percentage	$ln(p) = \theta X + \beta TC$	26%	778,038	0.003
Stetler et al. (2010)ˆ	6	Area (ha)	$ln(p) = \theta X + \beta_1 TC + \beta_2 TC^2$	16%	551,409	0.005
Walls et al. (2015)	5	Percentage	$ln(p) = \theta X + \beta TC$	10%	460,816	0.009

ˆ indicates a study in the Siriwardena et al. (2016) meta-analysis. One study (namely Coley (2005)) present in Siriwardena et al. (2016) was not included in our meta-analysis because the tree cover in Coley (2005) could not be reliably compared with the tree cover in the other studies.

$\theta X + \beta_1 TC + \beta_2 TC^2$, found in six studies has the elasticity equation formula, $\frac{\partial p}{\partial TC}\frac{TC}{p} = (\beta_1 + 2\beta_2 TC)TC$. Three studies that use the linear form,[3] $p = \theta X + \beta TC$, have the elasticity equation formula, $\frac{\partial p}{\partial TC}\frac{TC}{p} = \beta\frac{TC}{p}$. The log-log form in use by two studies, $\ln(p) = \theta X + \beta \ln(TC)$, has the elasticity formula, $\frac{\partial p}{\partial TC}\frac{TC}{p} = \beta$. The sample means for TC and p are plugged in where necessary to calculate the elasticities. The elasticity formulas differ slightly in two studies when the functional form includes interaction terms for tree cover and walkability (Drake-McLaughlin and Netusil, 2010) or other socio-demographic parameters (Saphores and Li, 2012). In those cases, plugging the sample means for the covariates that interact with tree cover into the modified elasticity formula generates the elasticity.

Challenges remain in the consistent measurement of tree cover across studies. Four of the 21 studies in the meta-dataset measure tree cover as an area (e.g. square feet, hectares, etc.) while the others report tree cover as a proportion or percentage of surface area. We convert the tree cover area to percentage tree cover by dividing the average area of tree cover in the circular buffer used by the primary study by the area of the circular buffer. Two studies that use tree cover area (Stetler et al., 2010; Dudley, 2012) have different sized circular buffers within their study that are incorporated into the calculation of the tree cover percentage.

Residential property price impacts differ by the distance of the tree cover from the property. Four primary studies consider tree cover on the property, either because no significant price effects were found from the off property tree cover or for analytical convenience. Tree cover on property offers greater amenities to the homeowner but also higher tree maintenance costs relative to tree cover off the property and farther away. Neighborhood tree cover adds less value than trees on property, but the costs associated with the trees off the property are arguably near zero. We standardize elasticities across studies with different assumptions for the proximity to tree cover by creating two distance bins, on-property and off-property tree cover within a mile from the home. Guignet et al. (2020) recently used this strategy in a meta-analysis of hedonic studies on water quality to separately consider the house price effects of waterfront and non-waterfront homes. A primary study that only considers on-property tree cover contributes an observation to the meta-dataset for the on-property bin. A study that examines on property and off property tree cover contributes an observation to each bin. There are 59 observations from 12 studies in the on-property bin, and 98 observations from 17 studies in the off-property bin.

The density of tree cover modifies the impact on a house price regardless of whether the tree cover is on the property or off the property. A nonlinear (i.e. quadratic) functional form for tree density in the hedonic equation to evaluate how the stock of the tree cover affects the house price is present in six primary studies. The implicit price of off-property tree cover appears to initially rise and then fall with tree density (Netusil et al., 2010; Sander et al., 2010). We consider three densities in the evaluation of the mean elasticities for on and off property tree cover: low density (0–10%), medium density (10–25%), and high density (>25%).

2.3. Summary statistics of the meta-dataset

Each of the 21 studies may analyze multiple tree canopy metrics, model specifications, and study areas, and as a result, we constructed a meta-dataset that contains 157 unique observations with the following characteristics (Table 2). The mean tree cover was 18% with range of 0.09 to 61.40%. The tree cover observations were equally divided among low (0–10%), medium (10–25%), and high (>25%) density classes. The majority (51%) of the observations were in the western US, with 19%, 18% and 11% in the Midwest, Northeast, and South, respectively (Fig. 1).

Some of the 21 hedonic studies examine how property value depends on the distance from tree canopy. As we noted above, residential property price impacts differ by the distance of the tree cover from the property. To handle distance, we divided the tree canopy observations into those that are on property and those that are off property and within 1600 m (1 mile). The majority (62%) of the observations were off property.

Socio-demographics of the primary study areas were obtained from the US Census Bureau by matching each observation to data for the corresponding jurisdiction and year of the decennial census. Median

[3] One study uses the linear-quadratic form with the elasticity formula $\frac{\partial p}{\partial TC}\frac{TC}{p} = (\beta_1 + 2\beta_2 TC)\frac{TC}{p}$.

Table 2
Descriptive statistics of tree cover, housing market, and methodological variables.

Variable	Mean	Std. Dev.	Min	Max	2020 Census[a]
Dependent variable					
Elasticity (%)	0.028	0.0628	−0.1319	0.3856	
Tree cover variables					
Tree cover (%)	17.62	12.65	0.09	61.4	
On property	0.38	0.49	0	1	
Low density (0–10%)	0.35	0.48	0	1	
Medium density (10–25%)	0.34	0.47	0	1	
High density (>25%)	0.32	0.47	0	1	
Coniferous tree type	0.1	0.3	0	1	
Decicuous tree type	0.05	0.22	0	1	
Mixed tree type	0.05	0.22	0	1	
Unspecified forest	0.8	0.4	0	1	
Housing market variables					
Median income (thousand 2020$)	69.32	29.29	24.26	135.02	62.84
Population density (1000 people per square mile)	1.81	1.91	0.008	7.88	0.01
College degree (% population)	22.5	5.70	7.20	32.6	32.1
Median age (years)	35.9	2.8	25.6	42.5	38.5
Hispanic (%)	8.60	8.0	1.8	33.9	18.5
Single Family Households (%)	53.2	10.3	25	68.9	40
Homeowners (%)	64.4	15.6	24.6	90.1	64.1
Homes built prior to 1990 (%)	75.6	11.4	45.7	94.4	
Rural-Urban Score (Very urban =1 to Very rural =9)	1.62	1.42	1	8	
Mean house sale price (2020$)	475,447	163,099	147,180	778,038	
Northeast	0.18	0.39	0	1	
Midwest	0.19	0.39	0	1	
South	0.11	0.32	0	1	
West	0.51	0.5	0	1	
Methodological variables					
Elasticity variance	0.0015	0.0103	5.49E-08	0.1255	
Unpublished	0.21	0.41	0	1	
Time trend (0 = 2002 to 17 = 2019)	8.67	4.05	0	17	
No spatial methods	0.18	0.39	0	1	
Spatial autocorrelation	0.41	0.49	0	1	
Spatial fixed effects	0.72	0.45	0	1	
Time fixed effects	0.42	0.49	0	1	
Linear	0.08	0.27	0	1	
Log-Linear	0.88	0.33	0	1	
Log-Log	0.04	0.21	0	1	

Note: Unweighted descriptive statistics for 157 observations from the 21 studies in the meta-dataset. Dummy variables are shown unless indicated otherwise.
[a] The national average for the 2020 decennial census.

household income (2020$ USD) is, on average, $69,320 in the areas examined by these primary studies. The national average for median income is lower at $62,840 (U.S. Census Bureau 2020). The percent of the population with a college degree is 22.5% on average, and population density is 1810 people per square mile. Finally, mean house prices in 2020 dollars using the Case-Shiller National Home Price Index is, on average, $475,447.

3. Methods

The methods section describes the calculation of the mean elasticities for unit value transfer, the tests for publication bias, the meta-regression model approaches for function transfer, and the techniques for out-of-sample transfer error prediction.

3.1. Mean elasticities

Mean elasticities are calculated in three ways: unweighted mean, a cluster weighted mean, and a random effect size weighted mean. Other than serving as useful summary measures, the mean elasticities have a potential application for unit value transfer. Function value transfer is still preferred over unit value transfer to control for heterogeneous differences across the study and policy sites (Stanley et al., 2013). However, the comparison of transfer errors across methodologies for benefit transfer has shown unit value transfer to occasionally outperform function transfer (Klemick et al., 2018). Our calculations include the mean elasticities used for unit transfer and the coefficient estimates from meta-regressions used for function value transfer.

We use Monte Carlo simulations to obtain for each observation the elasticity and corresponding standard errors for those elasticities. Simulations use the coefficient estimates, sample means of relevant explanatory variables, variances, and co-variances associated with tree cover and explanatory variables interacted with tree cover from the primary studies. Frequently, only the variance of a single coefficient is necessary for the simulations, but hedonic models that include quadratic and interaction terms require additional variances and co-variances. There is usually not a reporting of the full variance-covariance matrix, and we inquired with the primary study authors about these missing estimates for the Monte Carlo simulations.[4] The simulations take a hundred thousand random draws from the joint normal distribution of the relevant coefficients for each observation in the meta-dataset. The mean and standard error of the elasticity for each observation in the meta-dataset is computed from the resulting empirical distribution. The elasticity and standard error for each observation then go into the calculation of the unweighted mean, cluster weighted mean, and random effect size weighted mean for the meta-dataset.

An unweighted mean elasticity can be spurious because one primary study can contribute multiple observations from alternative hedonic specifications measuring the same fundamental value. The weight on an elasticity observation when there are multiple observations from a single study should be smaller to account for the lower level of unique information each observation contributes to the value of interest. A cluster-weighted mean recognizes that meta-observations from a common house transaction dataset for the same study period and area actually represent the same underlying value. We define each cluster as a unique house market, and a cluster is given the same overall weight regardless of the number of elasticity estimates in that cluster.

The cluster weighted mean elasticity for a distance bin b is $\overline{\varepsilon}_b$. Each elasticity estimate i, in bin b, for cluster j, is $\widehat{\varepsilon}_{ibj}$. The weights on $\widehat{\varepsilon}_{ibj}$ depend on, k_{bj}, the number of elasticity estimates in distance bin b in each cluster j. The number of clusters in the meta-dataset for bin b is K_b. Eq. (3) shows the cluster weighted mean elasticity:

$$\overline{\varepsilon}_b = \sum_{i=1}^{n} \sum_{j=1}^{K_b} \frac{\frac{1}{k_{bj}}}{\sum_{j=1}^{K_b} \sum_{i=1}^{k_{bj}} \frac{1}{k_{bj}}} \widehat{\varepsilon}_{ibj} \tag{3}$$

The final weighting approach uses the inverse variance, or random effect size (RES), of the elasticity estimates to put greater weight on more precise estimates (Nelson, 2015). Guignet et al. (2020) proposed a

[4] Despite two requests, we were not able to receive these missing estimates from the primary study authors.

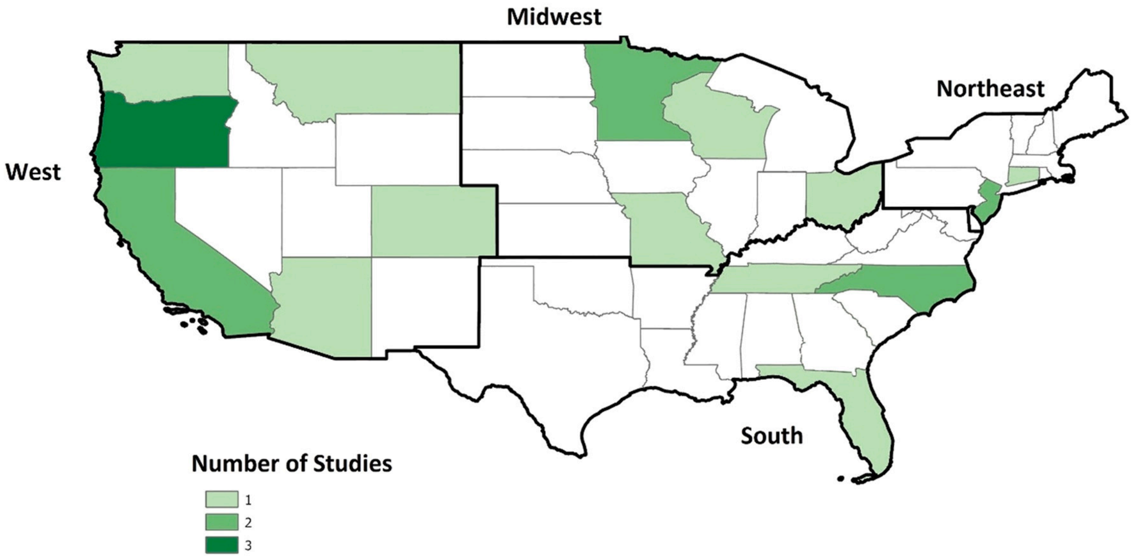

Fig. 1. Number of tree cover hedonic studies by state.

random effect size adjusted cluster (RESAC) weighting to spread evenly the weights across each cluster but also increase the weights to the elasticity estimates with less variance. Random effect size weights, w_{ibj}^{RES} whose derivation can be found in Nelson and Kennedy (2009), are inputs into the RESAC weights (Eq. (4)),

$$\omega_{ibj} = \frac{\frac{w_{ibj}^{RES}}{k_{bj}}}{\sum_{j=1}^{K_b}\sum_{i=1}^{k_{bj}}\frac{w_{ibj}^{RES}}{k_{bj}}} \tag{4}$$

The mean elasticity with the RESAC weights (Eq. (5)), $\overline{\overline{\varepsilon}}_b$, for the distance bin b is,

$$\overline{\overline{\varepsilon}}_b = \sum_{i=1}^{n}\sum_{j=1}^{K_b}\omega_{ibj}\widehat{\varepsilon}_{ibj} \tag{5}$$

3.2. Publication bias

There are four unpublished studies contributing thirty-one observations to the meta-dataset. We use a funnel asymmetry and precision effects test to check for publication bias (Stanley and Doucouliagos, 2012). Eq. (6) shows a weighted least squares regression using the inverse variance of the elasticities for the weights,

$$\widehat{\varepsilon}_{ibj} = \theta_0 + \theta_1 P_{ibj} + \boldsymbol{\varphi_0}\mathbf{v_{ibj}} + u_{ibj} \tag{6}$$

where $\widehat{\varepsilon}_{ibj}$ is the elasticity estimate i for bin b and cluster j, P_{ibj} is a measure of elasticity precision which is either the standard error or variance of the elasticity estimate, and $\mathbf{v_{ibj}}$ are controls for heterogeneity that include indicator variables for tree canopy proximity and density. Stanley and Doucouliagos (2012) show that a statistically significant non-zero estimate for $\widehat{\theta}_1$ is evidence of publication bias, and a better estimate for $\widehat{\theta}_1$ occurs when using the elasticity variance rather than the standard error for P_{ibj}. The reason that a non-zero estimate for $\widehat{\theta}_1$ means publication bias is that estimates with larger variance are unlikely to be statistically significant, and this diminishes the chance an article is published. The $\widehat{\theta}_0$ estimate is the elasticity after removing publication bias.

3.3. Meta-regression approach

Function transfer uses a meta-regression to account for heterogeneity in the elasticity estimate. Suppose the meta-regression model has this form,

$$\widehat{\varepsilon}_{ibj} = \beta_0 + \boldsymbol{\beta_1}\mathbf{x_{ibj}} + \boldsymbol{\beta_2}\mathbf{z_{ibj}} + e_{ibj} \tag{7}$$

where the explanatory variables include a vector of tree canopy and housing market variables, $\mathbf{x_{ibj}}$, and a vector of methodological variables, $\mathbf{z_{ibj}}$, that describe the model assumptions of the primary study (Table 1).

The tree canopy variables in $\mathbf{x_{ibj}}$ include dummies for whether the canopy is on the property, tree cover density (in particular, low density, medium density, or high density), and the type of urban forest (namely, coniferous, deciduous, mixed, or unspecified). Other housing market characteristics include demand side variables such as median income and age, population density, percentage of population with a college degree or Hispanic ethnicity and supply side variables such as the percentage of single-family households or homes built prior to 1990. There are also dummies for the degree of urbanization using the rural-urban continuum (ERS, 2013) and broad US regions, namely the Northeast, Midwest, South, or West.

Methodological variables in $\mathbf{z_{ibj}}$ reflect the hedonic model choices of the primary studies, and practitioners of function transfer can choose values for $\mathbf{z_{ibj}}$ that represent the preferred techniques. The elasticity variance included in $\mathbf{z_{ibj}}$ is to control for publication bias, and the value for this variable is set to zero for a function transfer application. Additional $\mathbf{z_{ibj}}$ variables are dummies of whether the study is unpublished and the functional form of the hedonic. Other dummy variables control for the presence of time fixed effects, spatial autocorrelation, or spatial fixed effects, respectively. Dummies are also set to one if there is no use of spatial lag, spatial autocorrelation, or spatial fixed effects while the value is zero otherwise. A categorical time trend variable with a range from zero to seventeen is based on the last recorded year of sale in the sample for the primary study (Johnston and Rosenberger, 2010). The year of publication of a primary study is always within a few years of the last transaction in the study's sample. The categorical time trend represents the change over time in empirical methods or awareness of tree canopy.

There is the potential problem of correlation among e_{ibj} for observations within the same housing market cluster. The drawback of a random effects model for estimation is that the cluster specific effect within e_{ibj} could be correlated with the observed independent variables, and this drawback is especially a concern when the elasticity variance is an independent variable in the meta-regression (Wooldridge, 2002). A fixed effects model is not feasible because many observations would be lost since explanatory variables frequently do not vary within a cluster. Another problem is that out-of-sample transfer would not be possible since the fixed effect is unavailable for housing markets not in the meta-dataset. Our approach to address the heteroskedasticity arising from the correlation among e_{ibj} is to estimate eq. (7) through RESAC weighted least squares using housing market cluster-robust standard errors.

Another meta-regression modeling approach for benefit transfer is to estimate the Mundlak regression model (Boyle and Wooldridge, 2018). Cluster specific effects are taken into account in the Mundlak model by including the cluster averages of the explanatory variables on the right-hand side of eq. (8).

$$\widehat{\varepsilon}_{ibj} = \beta_0 + \boldsymbol{\beta_1}\mathbf{x_{ibj}} + \boldsymbol{\beta_2}\mathbf{z_{ibj}} + \boldsymbol{\theta_1}\overline{\mathbf{x}}_\mathbf{j} + \boldsymbol{\theta_2}\overline{\mathbf{z}}_\mathbf{j} + v_{ibj} \tag{8}$$

where the cluster specific means for tree canopy and the housing market are $\overline{\mathbf{x}}_\mathbf{j}$ and for the methodological features are $\overline{\mathbf{z}}_\mathbf{j}$. Some of the cluster specific effects, potentially correlated with the explanatory variables, is represented by $\boldsymbol{\theta_1}\overline{\mathbf{x}}_\mathbf{j}$ and $\boldsymbol{\theta_2}\overline{\mathbf{z}}_\mathbf{j}$, where $e_{ibj} = \boldsymbol{\theta_1}\overline{\mathbf{x}}_\mathbf{j} + \boldsymbol{\theta_2}\overline{\mathbf{z}}_\mathbf{j} + v_{ibj}$. Whatever remains of the cluster specific effect goes into v_{ibj} and is assumed to be random and uncorrelated with the explanatory variables. The Mundlak model permits out-of-sample benefit transfer and utilizes the information embedded in all the explanatory variables, even for those variables without variation within clusters.

3.4. Out-of-sample transfer error

The out-of-sample transfer error is the difference between the calibrated transfer estimate and the observed estimate for the transfer site. The size of the transfer error depends on the similarity of the primary study sites and the population, the correspondence of the tree metrics and the policy context, and methods of benefit transfer applied (Rosenberger and Phipps, 2007). The acceptable level of error varies depending on the precision necessary for decision (e.g. higher transfer errors are fine for broad benefit-cost analyses and low transfer error required for litigation).

We calculate the out-of-sample transfer error through two approaches. The first approach is the comparison of a synthetically constructed elasticity observation for each distance bin b and housing market cluster j to a predicted elasticity from a meta-regression model using explanatory variables with similar construction to the synthetic elasticity. The second approach is the comparison of the true elasticities of an excluded cluster with the prediction based on a meta-regression estimated without the cluster.

The first approach constructs a synthetic mean elasticity for each distance bin b and cluster j using the inverse variance for the weights. Averages for the meta-regression explanatory variables for bin b and cluster j are calculated the same way using weights based on an inverse variance. The averages for the explanatory variables are put into the estimated meta-regression to generate a predicted elasticity. Similar weighting of the synthetic elasticity (i.e. the 'true' observation) and the predicted elasticity preserves the predictive performance of the meta-regression model (Guignet et al., 2020). Each iteration in the loop excludes one of the 21 housing market clusters. Once the iterations are complete, the calculation of the mean absolute value transfer error occurs.

The second approach also iterates over clusters, removes the actual elasticity observations within that cluster, and estimates the meta-regression model with the remaining sample to obtain the predicted elasticities for each observation in the excluded cluster (Lindhjem and Navrud, 2008). The downside of this approach is that inconsistent weighting across the predicted and observed elasticities can inflate the transfer error. To formally show the calculation of the transfer error, the notation for the predicted elasticity is $\widetilde{\varepsilon}_{ibj}$ and the observed (or synthetic) elasticity is $\widehat{\varepsilon}_{ibj}$. The absolute value of the percent difference in the predicted and observed elasticities (Eq. (9)) represents the transfer error,

$$\left|\%TE_{ibj}\right| = \left|\frac{\left(\widetilde{\varepsilon}_{ibj} - \widehat{\varepsilon}_{ibj}\right)}{\widehat{\varepsilon}_{ibj}}\right| \times 100 \tag{9}$$

The mean absolute value of the transfer error is the average of $|\%TE_{ibj}|$ for the observations across every distance bin b and cluster j.

4. Results

The results section describes the findings from the mean elasticity calculations and publication bias tests, the function transfer elasticity predictions from the meta-regressions (i.e. the weighted least square and Mundlak approaches), and the estimates of the out-of-sample transfer error. Our preferred meta-regression is Mundlak model 2 based on the lowest transfer error.

4.1. Mean elasticities

The RESAC weighted mean elasticity technique is the preferred method because it spreads the weights evenly across each housing market cluster but also increases the weights to the elasticity estimates with less variance. The results of the unweighted and cluster-weighted mean elasticity calculations are presented first for comparison. The second column of Table 3 shows the unweighted mean elasticity for the overall sample and by three tree cover densities – low density (0–10%), medium density (10–25%), and high density (25%+). Low density tree cover is the most commonly analyzed measure of tree cover in the literature with 55 elasticity estimates, followed closely behind by medium density with 53 estimates and high density with 49 estimates. We show for the overall sample the mean elasticities for on property tree canopy and off property tree canopy within one mile of the property. Also for the overall sample, we present the mean elasticities for each of the three tree cover density categories. Within each tree cover density category, we show the mean elasticity for on property versus off property tree canopy.

The unweighted mean elasticities for the overall sample are all statistically significant, and the elasticity magnitudes are similar for on property tree cover (0.0286%) and off property tree cover (0.0276%). As the density of tree cover increases in the overall sample, the unweighted mean elasticities are similar for low and medium density tree cover, 0.0176% and 0.0148% respectively, but the elasticity rises significantly to 0.0534% for the category of high density tree cover. A possible explanation for this is that high density tree cover increases the urban forest ecosystem services non-linearly, and the value of those services then is capitalized into home prices.

The low density tree cover category has a significant unweighted mean elasticity of 0.0356% from on-property tree canopy, but the elasticity from off-property tree canopy is statistically insignificant. When a neighborhood has low density tree canopy, the only way for the tree canopy to impact the house price is for the trees to be close to the house, namely on the property. The medium and high density tree cover categories have unweighted mean elasticities that are statistically significant for on property and off property tree canopy. The mean elasticities are higher for the off property than the on-property tree canopy, and the gap between the mean elasticities for the off and on property increases when going from the medium to high density categories. Homeowners in a neighborhood with medium density or higher tree canopy prefer additional tree canopy be off the property than on the property.

The mean elasticities using the cluster weights, where each cluster has the same weight regardless of how many elasticity estimates are in a cluster, appear in the third column of Table 3. The results are mostly similar for the overall sample, in particular elasticities are larger for neighborhoods with high tree canopy density rather than low or medium tree canopy density. One difference in the results for the overall sample is that the elasticity for off-property tree canopy is much higher than for

Table 3
Mean elasticity estimates.

Tree cover measure	Unweighted mean	Cluster-weighted mean	RESAC-weighted mean	Obs.	Studies
Overall					
On property	0.0286*** [0.0215, 0.0358]	0.0078*** [0.0001, 0.0156]	0.0030*** [0.0020, 0.0040]	59	12
Off property	0.0276*** [0.0188, 0.0365]	0.0411*** [0.0309, 0.0513]	0.0059*** [0.0037, 0.0082]	98	17
Low density (0–10%)	0.0176*** [0.0125, 0.0228]	0.0146*** [0.0109, 0.0182]	0.0018** [0.0007, 0.0030]	55	8
Medium density (10–25%)	0.0148*** [0.0103, 0.0192]	0.0108*** [0.0032, 0.0184]	0.0036*** [0.0026, 0.0045]	53	12
High density (25%+)	0.0534*** [0.0355, 0.0714]	0.0652*** [0.0446, 0.0858]	0.0099*** [0.0060, 0.0137]	49	12
Low density (0–10%)					
On property	0.0356*** [0.0255, 0.0457]	0.0147*** [0.0104, 0.0190]	0.0018*** [0.0009, 0.0026]	27	4
Off property	0.0003 [−0.0023, 0.0029]	0.0091*** [0.0050, 0.0131]	0.0023 [−0.0005, 0.0050]	28	6
Medium density (10–25%)					
On property	0.0093*** [0.0047, 0.0140]	0.0128*** [0.0040, 0.0217]	0.0029*** [0.0016, 0.0043]	14	7
Off property	0.0167*** [0.0109, 0.0225]	0.004 [−0.0048, 0.0128]	0.0035*** [0.0020, 0.0049]	39	9
High density (25%+)					
On property	0.0329*** [0.0159, 0.0500]	0.0094 [−0.0080, 0.0268]	0.0113*** [0.0065, 0.0162]	18	5
Off property	0.0660*** [0.0391, 0.0929]	0.1010*** [0.0701, 0.1319]	0.0125*** [0.0035, 0.0214]	31	8

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Confidence intervals at the 95% level are shown in brackets. The elasticity estimates presented in the table are unitless. Off property estimates for the implicit price of tree cover are derived from tree cover measurements taken within a maximum distance of approximately 1600 m (or 1 mile) from a property.

on property tree canopy. The low density tree canopy category still has the on property elasticity (0.0147%) larger than the off property elasticity (0.0091%), and both the on and off property elasticities are significant. The on property elasticity for the medium density tree canopy category (0.0128%) is larger than the statistically insignificant off property elasticity. The opposite is true of the high density category where the off property elasticity (0.1010%) is greater than the statistically insignificant on property elasticity. The cluster weighted mean elasticities suggest that only at the highest density category of tree canopy homeowners have a greater preference for off property tree canopy than on property tree canopy.

The elasticities using the random effect size weights with cluster adjustment (RESAC) are smaller than the unweighted or cluster weighted elasticities, but exhibit similar trends as the elasticities from the other weighting approaches (Table 3). For the overall sample, the off property RESAC elasticity (0.0059%) is greater than the on property elasticity (0.0030%), and there is a steady increase in the RESAC elasticity from the low density (0.0018%) to the high density (0.0099%) categories. These findings highlight the earlier observation that the elasticities are largest (and hence property values increase the most) for off property tree canopy in neighborhoods that have a significant density of tree canopy. But an exception to the overall sample findings occur when the tree canopy is at a low density. In that case, the on property elasticity is positive and significant while the off property elasticity is positive but not statistically different from zero. However, for neighborhoods with medium or high tree canopy density, the RESAC findings align once more with the findings of the overall sample, and the alignment intensifies as tree canopy density increases.

4.2. Publication bias

We find evidence of publication bias in the meta-dataset (Table 4) based on the statistically significant coefficient on the standard error in column “(1)” and on the coefficient on elasticity variance in columns “(2)” to “(4)”. The statistically significant constant in columns “(2)” to “(4)” indicate that tree canopy has a statistically significant effect on house value, once there is a control for publication bias (that is, through the inclusion of the elasticity variance in the simple meta-regression model). The statistically significant constant term in column “(3)” indicates the elasticity for off property tree canopy is 0.0031% and the sum of the on property only coefficient and the constant term indicates an elasticity of 0.0012%. The column “(4)” coefficient results indicate that for neighborhoods with low or medium density the on property and off property elasticities are 0.0008% and 0.0027%, respectively. However, locations with high density tree cover have respectively on property and off property elasticities of 0.0101% and 0.012%. These elasticities are close to the mean RESAC elasticities calculated in Table 3.

Table 4
Publication bias tests with simple meta-regression models.

Variables	Model number (1)	(2)	(3)	(4)
Elasticity variance		16.9098*** (6.266)	16.6033*** (6.193)	14.5579** (6.073)
On property			−0.0019** (0.001)	−0.0019** (0.001)
Medium density (10–25%)				0.0016 (0.001)
High density (25%+)				0.0093*** (0.003)
Elasticity standard error	1.4808*** (0.268)			
Constant	0.0006 (0.000)	0.0019*** (0.000)	0.0031*** (0.001)	0.0027*** (0.001)
R-squared	0.164	0.045	0.073	0.130
Log-likelihood	614.26	603.73	606.11	611.14

Dependent variable: property value elasticity with respect to the percentage of tree cover. Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Number of observations: 157. Standard errors in parentheses. Estimation is through weighted least squares in Stata 15 with analytical weights equal to the inverse variance of the elasticity estimates.

4.3. Meta-regressions

The first series of meta-regression results in Table 5 are for the weighted least squares (WLS) model with cluster-robust standard

Table 5
Meta-regressions with weighted least squares (WLS).

Variables	Model number (1)	(2)	(3)
Tree cover	−0.0025 (0.002)	−0.0039** (0.002)	−0.0031* (0.002)
Coniferous tree type	−0.0510** (0.023)	0.1173 (0.072)	0.3349** (0.128)
Deciduous tree type	−0.0398** (0.019)	0.1523** (0.067)	0.3734*** (0.121)
Mixed tree type	−0.0602** (0.023)	0.1023 (0.072)	0.3242** (0.131)
Midwest		0.031 (0.048)	0.0416* (0.024)
South		0.0099 (0.042)	0.0857* (0.046)
West		−0.0219 (0.054)	−0.043 (0.043)
On property	−0.0191 (0.023)	−0.0058 (0.011)	0.0036 (0.004)
Medium density	0.0224 (0.019)	0.0431** (0.019)	0.0312** (0.014)
High density	0.078 (0.047)	0.0933* (0.045)	0.0725 (0.042)
On property*Medium density	0.0113 (0.019)	−0.0103 (0.012)	−0.0140** (0.007)
On property*High density	−0.0036 (0.021)	−0.0339* (0.019)	−0.0414*** (0.014)
Rural-Urban Score (=2)		0.0161* (0.009)	0.0802*** (0.026)
Rural-Urban Score (=3)		−0.0105 (0.041)	0.0798** (0.033)
Rural-Urban Score (=6)		0.2343*** (0.063)	0.8685*** (0.23)
Rural-Urban Score (=8)		0.3117*** (0.091)	1.0045*** (0.27)
Population density	−0.0056 (0.005)	0.0007 (0.004)	0.0196** (0.007)
Homes built prior to 1990	0.1364* (0.071)	−0.001 (0.089)	−0.3832** (0.162)
Median age	−0.0086 (0.006)	−0.0071 (0.007)	−0.0181*** (0.006)
Hispanic	0.1199 (0.151)	−0.6491** (0.233)	−2.5104*** (0.74)
Single Family Households	−0.2335 (0.161)	0.4612* (0.252)	1.8989*** (0.585)
College degree	−0.2523 (0.17)	−0.105 (0.145)	−0.3137** (0.124)
Median income	0 (0)	0.0024** (0.001)	0.0103*** (0.003)
Homeowners	0.3548 (0.237)	−1.1235** (0.484)	−4.1656*** (1.256)
Elasticity variance	19.1968 (11.836)	17.6529 (12.418)	9.4869 (6.592)
Unpublished	0.0365** (0.016)	0.0357** (0.013)	−0.0627 (0.056)
Time trend	0.0018 (0.003)	0.0089** (0.004)	0.0180*** (0.005)
No spatial methods			−0.0722 (0.043)
Log-Linear			0.2779*** (0.071)
Log-Log			0.2651*** (0.075)
Spatial autocorrelation			−0.0187 (0.013)
Spatial fixed effects			−0.0896* (0.045)
Time fixed effects			0.0519 (0.035)
Constant	0.1747 (0.156)	0.5733** (0.254)	1.7332*** (0.474)
Adjusted R-squared	0.269	0.422	0.540
Log-likelihood	460.5072	483.0452	504.8300

Dependent variable: property value elasticity with respect to the percentage of tree cover. Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors are in parentheses. Number of observations: 157. Estimation is through weighted least squares in Stata 15 with analytical weights equal to RESAC weights.

errors.[5] The RESAC weighting approach in the WLS model puts more weight within a cluster on the elasticity estimates that are more precise while ensuring that each of the 21 housing market clusters has an equal influence. The Model 1 explanatory variables include the tree canopy features such as the tree canopy percentage, on property indicator for the tree canopy, the type of tree cover (e.g. deciduous), the density categories of the tree canopy (i.e. medium and high since the omitted category is low density), and interacted variables between the indicator of on property tree canopy and the tree canopy density categories. Other key explanatory variables represent the housing market and surrounding population (e.g. population density and median age, percentage of single family households) and a subset of the methodological attributes (e.g. whether the study was published).

Most explanatory variables in Model 1 have no significant effect on the elasticity estimates. The indicators for each type of tree cover (e.g. deciduous, coniferous, mixed) have statistically significant and negative coefficients relative to the omitted unspecified tree cover most commonly found in the literature. The percentage of houses built before 1990 has a positive and significant coefficient. All these significant coefficients in Model 1 however switch sign in the Models 2 and 3 that have additional controls for heterogeneity. The unpublished dummy is significant in both Models 1 and 2, and the coefficient suggests that the elasticity estimates for unpublished studies are larger by about 0.036% points. The sign switches for the unpublished dummy in Model 3, however, and loses significance.

Model 2 has controls for location using indicator variables for four US regions (Northeast as the omitted category) and five rural-urban continuum scores (most populous score on the continuum as the omitted category), and as a result, more explanatory variables have significant coefficients. The dummies for the medium and high tree cover densities are significant, and the elasticity estimates are 0.0431 and 0.0933 percentage points higher, respectively. Although only statistically significant in WLS models 2 and 3, the negative coefficient corresponding to the percentage of average tree cover (−0.0039 in Model 2) indicates that homes lose value as tree cover increases within a density category. This might be diminishing marginal returns from tree canopy after a certain tree cover density threshold is reached. Netusil et al. (2010) find additional tree cover can lower house value even if tree cover density is as low as 13% although the average tree cover density when tree canopy starts to discount the house value is 21%. Also, the premium of the high density tree canopy applies only to off-property tree canopy based on the statistically insignificant 0.0594 (p-value = 0.21), which is the sum of the high density and the corresponding on property interaction term coefficient estimates. The result is understandable because on property tree cover at a high density raises maintenance expenses without increasing benefits much beyond what the neighborhood tree cover already provides.

Less populous locations, according to the rural-urban continuum (RUCC) scores, have higher elasticities. The most rural location has a coefficient that suggests the elasticity estimate is higher by 0.312 percentage points. Houses in markets where a large proportion of the population has a Hispanic background have a lower elasticity by −0.649 percentage points. A percentage increase in the single family households within a housing market raises the elasticity by 0.461 percentage points. Single-families often purchase property for the long term, and the benefits they receive from tree cover over the long horizon capitalize into house values. However, the coefficient on the home ownership dummy indicates a lower elasticity estimate by −1.124%. The ownership of

[5] Boyle and Wooldridge (2018) indicate the WLS will not solve the heteroskedasticity problem if RESAC weights ignore a source of error. The RESAC weights are even across each cluster (potentially problematic if the error varies by cluster) and places greater weight on the elasticity estimates with less variance. With incorrect weights, the WLS estimator is not a consistent estimator of the predictor.

homes other than single family houses diminishes the effect of tree cover on house value. Owners of multi-residential properties may only plan to live at the property for a short while, and fewer benefits from tree cover capitalize into those homes. Each additional thousand dollars in household median income raises the elasticity estimate by 0.0024%. The time trend is significant and positive, and this suggests the elasticity estimates have been rising over time.

We predict the average elasticity from the WLS meta-regressions using the cluster weighted mean values of the covariates except for the elasticity variance set to zero and the time trend set to 17 (i.e. the most recent year, 2019, in the metadata) to represent the best practices of benefit transfer and the most recent methods and data. The Model 2 prediction (which has the lowest out-of-sample error based on synthetic observation for excluded clusters) for the average elasticity of off-property tree cover is 0.0059 ($p = 0.37$), which means that a 1% increase in the tree cover percentage within a mile of a property (i.e. an increase in the mean tree cover of 0.18%) results in 0.0059% increase in home value (i.e. about \$28). The elasticity for on property tree cover in a neighborhood is 0.0031 ($p = 0.31$), so that an increase in the on property percentage of tree canopy by 1% increases the home value by \$15.

All the methodological attributes are in Model 3, and the significant variables in Model 2 are found to be robust to the additional variables of the third model. Several more significant variables are present in Model 3. All the dummies for tree cover type have positive and significant coefficients, and the deciduous type has the largest effect (0.373%) followed by coniferous and then mixed tree cover. The coefficients on the U.S. regions suggest that elasticities are higher in Midwest and South than in the Northeast. The evidence that off-property tree canopy contributes more to house value strengthens in Model 3 based on the now negative and significant coefficient for the medium density and on property interaction term. An additional thousand people per square mile (i.e. greater population density) increases the elasticity estimate by 0.019 percentage points. A percentage increase in houses built before 1990 lowers the elasticity estimate (−0.383%) as does the percentage population with a college degree (−0.314%). Statistically significant attributes related to the methodologies in the hedonic model used by the primary studies in Model 3 indicate that log-linear (0.278%) and log-log (0.265%) models have higher elasticities compared to a linear hedonic model (i.e. the omitted category). Primary studies that use spatial fixed effects in their model have a lower elasticity (−0.089%).

Now we compare the WLS results to the Mundlak model meta-regression results in Table 6. The coefficient on the percentage of average tree cover is negative and significant in Mundlak model 1, similar to the WLS models 2 and 3. Mundlak models 2 and 3 have negative and significant coefficients associated with the average percentage of tree cover. The results then consistently show a decline in the elasticity from more tree cover within a density category. The medium and high density dummies or their cluster averages are significant and positive in all Mundlak models. The coefficient on the interaction term for on property and high density is consistently negative and significant for all Mundlak models, and this is also the case for the on property and medium density interaction term for Mundlak models 2 and 3. The cluster average for the on property dummy is significant and negative in the Mundlak models 2 and 3. The evidence is stronger for an off-property tree cover premium in the Mundlak than the WLS results. The type of tree cover does not show much of an effect on the elasticity in the Mundlak model, and the coefficient on the cluster average for the conifer type is even negative and significant (i.e. the opposite of the WLS results). The mixed results for tree type are perhaps not surprising considering that the omitted category is unspecified tree type.

The population density and its cluster average have an opposite sign, but there is a net positive coefficient for the Mundlak models 2 and 3 (e.g. -1.922 + 2.035 = 0.113 for model 3) relevant for out-of-sample inference. The net positive coefficient for population density in the Mundlak model has the same sign as the WLS result. The coefficient on the variables corresponding to the percentage of homes built before

Table 6
Meta-regressions with the Mundlak model.

Variables	Model number		
	(1)	(2)	(3)
Tree cover	−0.0031** (0.001)	−0.0023 (0.001)	−0.0022 (0.001)
Tree cover cluster mean	0.0019 (0.001)	−0.0365*** (0.004)	−0.0371*** (0.009)
Coniferous tree type	−0.0277 (0.039)	0.1522 (0.119)	0.184 (0.307)
Coniferous tree type cluster mean	0.0425 (0.041)	−0.8544*** (0.14)	−0.8603** (0.39)
Deciduous tree type	−0.0048 (0.033)	0.1839* (0.106)	0.2148 (0.302)
Mixed tree type	−0.0387 (0.039)	0.1449 (0.124)	0.1769 (0.31)
Midwest		−0.7448*** (0.049)	−0.7358*** (0.129)
South		−0.5188*** (0.058)	−0.5406*** (0.193)
West		−0.8684*** (0.056)	−0.8746*** (0.167)
On property	−0.0123 (0.012)	0.004 (0.003)	0.0036 (0.003)
On property cluster mean	0.0182 (0.029)	−0.3030*** (0.033)	−0.3073*** (0.087)
Medium density	0.0303*** (0.011)	0.0205* (0.011)	0.0197* (0.011)
Medium density cluster mean	−0.0099 (0.023)	1.0498*** (0.099)	1.0919*** (0.299)
High density	0.0759** (0.035)	0.0476 (0.035)	0.046 (0.035)
High density cluster mean	−0.008 (0.048)	1.4706*** (0.126)	1.4950*** (0.335)
On property*Medium density	0.002 (0.012)	−0.0105** (0.004)	−0.0100** (0.004)
On property*High density	−0.0258* (0.014)	−0.0409*** (0.011)	−0.0396*** (0.011)
Rural-Urban Score (=2)		0.0214 (0.018)	0.0268 (0.02)
Rural-Urban Score (=2) cluster mean		0.2794*** (0.038)	0.2855** (0.118)
Rural-Urban Score (=3)		0.2703*** (0.033)	0.2778** (0.111)
Rural-Urban Score (=3) cluster mean		1.0406*** (0.053)	1.0290*** (0.111)
Rural-Urban Score (=6)		−0.8819*** (0.129)	−0.9551** (0.422)
Rural-Urban Score (=8)		−0.0313 (0.026)	−0.0565 (0.083)
Population density	−0.4070*** (0.079)	−1.9040*** (0.16)	−1.9227*** (0.573)
Population density cluster mean	0.4051*** (0.075)	2.0184*** (0.164)	2.0348*** (0.586)
Homes built prior to 1990	0.1296 (0.085)	−0.8331*** (0.198)	−0.9139 (0.62)
Median age	−0.1450*** (0.023)	−0.7488*** (0.06)	−0.7547*** (0.219)
Median age cluster mean	0.1398*** (0.023)	0.8518*** (0.07)	0.8607*** (0.253)
Hispanic	−0.1298 (0.246)	−1.0237*** (0.081)	−0.9736*** (0.089)
Single Family Households	0.0684 (0.07)	−1.2801*** (0.307)	−1.4124 (0.915)
College degree	−0.0196 (0.235)	−2.5043*** (0.17)	−2.5082*** (0.409)
Median income	−0.0002 (0)	0.0001 (0)	−0.0003 (0.002)
Elasticity variance	20.3022* (12.08)	7.4985* (4.244)	6.7313* (3.726)
Time trend	0.0012 (0.002)	−0.0026*** (0)	−0.0017*** (0)
No spatial methods			0.0184*** (0.006)
Log-Linear			0.0060** (0.003)
Spatial autocorrelation			−0.0151 (0.012)
Spatial fixed effects			0.0049 (0.016)

(*continued on next page*)

Table 6 (*continued*)

Variables	Model number		
	(1)	(2)	(3)
Time fixed effects			−0.0179 (0.014)
Constant	0.078 (0.188)	−1.3697*** (0.068)	−1.3342*** (0.086)
Log-likelihood	5.88	6.60	6.64

Dependent variable: property value elasticity with respect to the percentage of tree cover. Note: *** p < 0.01, ** p < 0.05, * p < 0.1. Robust standard errors are in parentheses. Number of observations is 157. First there is a calculation of cluster means for independent variables that vary within each of the 21 clusters. Estimation uses a multi-level mixed effects linear regression with RESAC weights and cluster-level residuals that correlate. A cluster mean term is not included for a variable if there is no within cluster variation for the variable or if the cluster mean term is dropped in Stata due to multicollinearity.

1990, the percentage of the population with a Hispanic background, the percentage of the population with a college degree, and the dummy for the log-linear hedonic specification all have the same sign as the WLS result.

The mean age, similar to population density, has a coefficient of opposite sign from its cluster average. The net positive coefficient on mean age for Mundlak models 2 and 3 differs in sign from the WLS result. A couple other variables have coefficients with a different sign from those of the WLS models, and these are the percentage of single-family households (though not significant in two of the three models) and the time trend. The location specific coefficients for the U.S. regions and RUCCs in the Mundlak models also different. The elasticities are lower in every U.S. region compared to the Northeast with the lowest elasticity in the West (−0.874%). The RUCCs indicate that the less populous regions have lower elasticities (−0.955% for a RUCC score of 6 in the Mundlak model 3). The highest elasticity corresponds to the RUCC score of 3 based on the coefficients for that dummy variable and its cluster average. Other differences are that the median income variable is not significant while the elasticity variance and no spatial method variables are significant.

The discrepancy of the findings across the Mundlak and WLS models relate partly to the omission due to multi-collinearity of the variables for the percentage of homeowners (i.e. correlated with single-family households) and the dummy for unpublished studies (i.e. correlated with the time trend). There is no a priori preferred specification since an argument supported by economic theory could be made for the inclusion of the variables missing in either the WLS model or the Mundlak model. The elasticity predictions in the Mundlak model 2 are a bit lower for off and on property tree canopy than in the WLS model 2. The predicted elasticities for an increase by 0.18% in the mean tree cover is 0.0036 for off-property (i.e. increase of $17) and 0.0029 for on-property (i.e. increase of $14), respectively.

4.4. Out-of-sample transfer error

In Table 7, the median absolute transfer errors are shown for the WLS and Mundlak models. The first row shows the transfer errors from a comparison with a synthetically constructed observation for each excluded cluster, and the second row shows the transfer errors from a comparison with each of the actual observations in an excluded observation. The median absolute transfer error among the two rows range from 71% to 89% in the WLS models and 29% to 110% in the Mundlak models. The Mundlak models 2 and 3, with better controls for cluster-specific effects, outperform the simpler WLS models. The Mundlak model 2 is most appealing for function transfer since the median transfer error of that model is the lowest in both rows, and the model includes the controls for the regional heterogeneity found to be large and significant.

Table 7
Out-of-sample transfer errors.

Model	Comparison with synthetic observations for excluded clusters ($n = 21$)	Comparison with excluded cluster observations ($n = 157$)
WLS (1)	83.47%	88.77%
WLS (2)	71.28%	84.73%
WLS (3)	73.06%	78.03%
Mundlak (1)	109.78%	82.71%
Mundlak (2)	28.59%	54.49%
Mundlak (3)	46.33%	60.46%

Calculation of the out-of-sample transfer error occurs through iterative omission of the twenty-one clusters followed by estimation of the model with the remaining clusters. With the predicted elasticity, there is a transfer error associated with the synthetic observations or the actual observations of the cluster excluded.

No improvement in predictive performance occurs in the Mundlak model 3 with the extra methodological variables.

Kaul et al. (2013) report mean and median transfer errors of 42% and 33%, respectively, from a sample of 925 transfer errors collected from studies published over 1990 to 2009. In a review of benefit transfer studies of outdoor recreation, Smith and Pattanayak (2002) find a mean transfer error of 80%. Comparing transfer errors between countries using contingent valuation, Ready et al. (2004) find transfer error between 37 and 39%. Rosenberger (2015) uses function transfer and finds a median 36% transfer error while unit transfers have a median transfer error of 45%. Vista and Rosenberger (2013) take sport fishing values from 140 primary studies and find median transfer errors of 45% to 55%. The transfer errors from our WLS models are on the high-end, but the Mundlak models 2 and 3 have transfer errors below or close to the median of other meta-analyses.

5. Discussion

We begin by comparing of our meta-analysis of hedonic property value studies to a tree cover meta-analysis by Siriwardena et al. (2016). A major difference is that we include 58 new observations on the implicit price of tree cover from seven new studies. Another difference is that we divide the analysis into discrete components depending on whether the tree cover is on or off property and the density in the neighborhood. Our discrete approach allows for a closer examination of how proximity and density of tree cover affect home values within a neighborhood. At the lowest tree cover density (less than 10%), on-property tree cover increases home value while off-property tree cover has no statistically significant effect. At medium and high densities of tree cover, the off-property tree cover has a larger influence than on-property tree cover. Siriwardena et al. (2016) uses a continuous quadratic variable for the percentage of tree cover from the primary study and also for the county where the study is located with US Forest Service data. They find that the tree cover percentage that maximizes home value is larger for county wide tree cover than for neighborhood tree cover and conclude that off property tree cover has more value. Our discrete approach shows that the greater influence from off property than on property tree cover is most significant when tree cover density is high.

The Mundlak model 2 has lowest transfer error associated with out-of-sample prediction. We prefer the Mundlak model because the WLS approach is problematic because heteroskedasticity will persist if the RESAC weights are incorrect. The Mundlak model finds that the elasticities are larger in the Northeast and South than the Midwest and West. The elasticities in the West disproportionately come from the Pacific Coast, and more studies from the Rocky Mountain West would help in discerning region effects on the elasticities. Siriwardena et al. (2016)

find the largest implicit prices are in the East. Population density has a net positive influence on elasticity in our study while Siriwardena et al. (2016) find no effect. People who live in areas with high population density prefer tree cover perhaps because the tree cover provides more relative shelter in busy areas. Metro counties with a million people or less (RUCC scores of 2 and 3) have the largest elasticities. Both Siriwardena et al. (2016) and our study find median income has no significant influence. Our meta-analysis indicates median age has a net positive influence on the elasticity. The percent of the population with a college degree has a negative influence, and more education may lead people to prefer other amenities (e.g. lakes, museums, vacations, etc.) rather than tree cover. Evidence of racial preference also arises, with the percent of the population of Hispanic ethnicity having a negative effect on the elasticity.

We can calculate from our preferred Mundlak model 2 the value of a 1% increase in tree cover on property and the value of a 1% increase in tree cover within a circular mile of the home. Our Mundlak model 2 predicts an $8.88 increase in the value of a single-family home in the Midwest for an on-property increase in tree cover of 0.18%.[6] Assuming that the single-family home is on a half-acre lot (21,780 ft^2) with an average tree cover of 18% (3920 ft^2) (Table 2), we find that a 1% increase in the percentage tree cover amounts to an increase of 39 ft^2. Suppose that a 24-in. dbh green ash tree has a crown radius of 35 ft. and a crown area of 962 ft^2. A 1% increase in tree cover is equivalent to 0.04 additional 24-in. green ash trees on the property (39/962 = 0.04). The increase in property value for one green ash tree on the property is $8.88/0.04 = $222. Our Mundlak model 2 also predicts a $76.2 increase in the value of a single-family home in the Midwest for a 0.18% increase in tree cover within a mile of the home.[7] A circular area with 1-mile radius has 87.6 million ft^2. Using the average tree cover of 18% (Table 2), we find that trees cover 15.8 million ft^2, and a 1% increase in the percentage tree cover amounts to an increase of 158,000 ft^2. Suppose again a 24-in. dbh green ash tree has a crown radius of 35 ft. and a crown area of 962 ft^2. A 1% increase in tree cover is equivalent to 164 additional 24-in. dbh green ash trees within a mile of the home (158,000/962 = 164).

What is the total value of a 1% increase in tree cover in a neighborhood? Here, we need to calculate the increase in value of all the homes in the neighborhood, and so we need an estimate of housing density. According to the 2019 US Census, there are 2176 households per square mile in St. Paul, MN. If we assume the neighborhood is a circular mile in size, then there are 2176 * 3.14 = 6833 homes in the neighborhood (there are 3.14 mile^2 in a circular mile). If each home benefits from the 1% increase in tree cover in the circular area, then the aggregate increase in property value is 6833 * $76.2 = $520,675, for the off-property component of the tree cover. In addition, the aggregate increase in property value is 164 * $222 = $36,408 for the on-property component of tree cover, again assuming the 1% increase in tree cover is composed of 164 24-in. dbh ash trees. Adding those two components, the total value of a 1% increase in tree cover in the circular mile area is $557,083 or $277 per acre of land.

As the hedonic literature increases its focus on the spatial features of the non-market goods, more meta-observations for distance bins farther than a mile from a property could increase the thoroughness of the meta-analysis. Another limitation in meta-dataset is in the geographic areas covered with a need for more studies outside of the western US. Likewise, more studies should be conducted outside of metropolitan areas. More information about how home values respond to the type of tree cover (e.g. deciduous, coniferous, mixed) is also needed. In order to examine the tree cover density that maximizes home value, more studies need to be in areas with tree density above 40%. The largest elasticity occurs in the high density category (i.e. greater than 25%), but there are not enough studies in the places with greater tree density to accurately determine if and when the elasticity starts to plateau or decline. Augmentation of our meta-dataset requires additional studies that use the percentage of tree cover metric. However, new studies should consider other tree metrics to understand how ecosystem services from trees that accrue to homeowners influence the property values.

The information in this benefit transfer tool can be coupled with models that predict the values associated with urban trees (e.g., i-Tree; www.itreetools.org). The coupling requires a compatible tree metric (e.g. the percentage of tree cover). The creation of a meta-dataset of property values with alternative tree metrics (e.g. the number of trees, tree biomass, leaf area, and species composition) would enhance the robustness of the benefit transfer options available to policy makers. Potential users of the Mundlak model 2 for benefit transfer could collect publicly available tree cover and housing market data for the policy site and decide on values for the methodological variables (e.g. mean values from Table 2, elasticity variance set to zero, and the time trend set to 17). If no data for the meta-regression covariates are available, the RESAC-weighted mean values for the elasticities in Table 3 can be used.

6. Conclusion

Urban forest management decisions are mostly made by local governments. Our benefit transfer tool could help local decision makers evaluate the benefits of proposed strategies that address local threats from invasive pests and diseases and from climate change that could alter urban tree canopy through changes in forest structure and vitality. At the national level, coordination and funding activities related to urban forestry are led by organizations such as the USDA Forest Service Urban and Community Forestry Program (https://www.fs.usda.gov/managing-land/urban-forests/ucf) and the National Urban and Community Forestry Advisory Council (https://www.fs.usda.gov/managing-land/urbanforests/ucf/nucfac). Our benefit transfer tool, which accounts for local differences in the housing market, the structure of urban forests, and the hedonic methodologies employed, could provide useful information to national organizations about the relative benefits of proposed changes in urban and community forestry programs around the country. These estimates could then be used to prioritize regional investments.

Our meta-analysis of property value and tree canopy uses newer methodological techniques than the earlier meta-analysis of Siriwardena et al. (2016), but both studies reach the conclusion that the off-property tree canopy is more valuable than on-property tree canopy. Other than the Mundlak model 2, the transfer errors of the meta-regression are above average, and it may be beneficial to use the second Mundlak model for function transfer to inform urban forest policy. Despite a paucity of primary studies that consider tree cover densities greater than 30%, specific tree cover types (e.g. deciduous, coniferous, mixed), and locations other than the Western US, we believe our benefit transfer tool offers practitioners with valuable information on the contribution of tree cover to property value. Without the resources to conduct an original study and without an existing study that matches the policy circumstances, then the findings of our meta-analysis can help appraise the property value effects of urban forest changes.

[6] The RESAC weighted predicted elasticity for on property tree cover in the Midwest using the Mundlak model 2 is 0.001868. Assuming a mean tree cover of 17.62% (i.e. approximately 18%) from Table 2, then a 1% increase in the percentage of tree cover is a 0.01*18% = 0.18%. Using the predicted elasticity, a 1% increase in the percent of mean tree cover (i.e. an increase of 0.18%) corresponds to a 0.001868% increase in single-family home value. Assuming a mean home value of $475,447 from Table 2, the dollar value of a 1% increase in the on property mean tree cover is 0.00001868*$475,447 = $8.88.

[7] The predicted elasticity for the off property tree cover in the Midwest is 0.0160348 for the Mundlak model 2. The dollar value of a 1% increase in the off property mean tree cover is 0.000160348*$475,447 = $76.24.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. List of all studies considered for the meta-analysis

A.1. Studies included

1. Cho, S. H., Poudyal, N. C., & Roberts, R. K. (2008). Spatial analysis of the amenity value of green open space. Ecological economics 66(2–3), 403–416.
2. Dimke, K. C. (2008). Valuation of tree canopy on property values of six communities in Cincinnati, Ohio (Doctoral dissertation, The Ohio State University).
3. Drake-McLaughlin, N., & Netusil, N. R. (2010, February). Valuing walkability and vegetation in Portland, Oregon. In Benefits and Costs of Natural Resources Policies Affecting Public and Private Lands Twenty-Second Interim Report and Proceedings from the Annual Meeting (Vol. 2, p. 173). Department of Agricultural and Resource Economics Tucson, AZ.
4. Dudley, T. (2011). The Value of Landscape Amenities: Contrasting Feature Proximity and View.
5. Donovan, G.H., Landry, S., Winter, C. (2019). Urban trees, house price, and redevelopment pressure in Tampa, Florida. Urban Forestry & Urban Greening 38: 330–336.
6. Escobedo, F.J., Adams, D.C., Timilsina, N. (2015). Urban forest structure effects on property value. Ecosystem Services 12: 209–217.
7. Holmes, T. P., Murphy, E. A., & Bell, K. P. (2006). Exotic forest insects and residential property values. Agricultural and Resource Economics Review, Vol. 35 (1): 155–166.
8. Holmes, T. P., Murphy, E. A., Bell, K. P., & Royle, D. D. (2010). Property value impacts of hemlock woolly adelgid in residential forests. Forest Science, 56(6): 529–540.
9. Huggett Jr., R. J. (2004). Fire in the Wildland-Urban Interface: An Examination of the Effects of Wildfire on Residential Property Markets.
10. Kadish, J., & Netusil, N. R. (2012). Valuing vegetation in an urban watershed. Landscape and Urban Planning, 104(1): 59–65.
11. Kim, Y. S., & Wells, A. (2005). The impact of forest density on property values. Journal of Forestry, 103(3): 146–151.
12. Li, X., Holmes, T. P., Boyle, K. J., Crocker, E. V., & Nelson, C. D. (2019). Hedonic Analysis of Forest Pest Invasion: the Case of Emerald Ash Borer. Forests, 10(9): 820.
13. Mansfield, C., Pattanayak, S. K., McDow, W., McDonald, R., & Halpin, P. (2005). Shades of green: measuring the value of urban forests in the housing market. Journal of forest economics, 11(3): 177–199.
14. Mei, Y., Hite, D., & Sohngen, B. (2017). Demand for urban tree cover: A two-stage hedonic price analysis in California. Forest Policy and Economics, 83: 29–35.
15. Netusil, N. R., Chattopadhyay, S., & Kovacs, K. F. (2010). Estimating the demand for tree canopy: a second-stage hedonic price analysis in Portland, Oregon. Land Economics, 86(2): 281–293.
16. Paterson, R. W., & Boyle, K. J. (2002). Out of sight, out of mind? Using GIS to incorporate visibility in hedonic property value models. Land economics, 78(3): 417–425.
17. Price, J. I., McCollum, D. W., & Berrens, R. P. (2010). Insect infestation and residential property values: A hedonic analysis of the mountain pine beetle epidemic. Forest Policy and Economics, 12(6): 415–422.
18. 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. Ecological Economics, 69(8): 1646–1656.
19. Sander, H. A., & Haight, R. G. (2012). Estimating the economic value of cultural ecosystem services in an urbanizing area using hedonic pricing. Journal of environmental management, 113: 194–205.
20. 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. Landscape and urban planning, 104(3–4): 373–387.
21. Stetler, K. M., Venn, T. J., & Calkin, D. E. (2010). The effects of wildfire and environmental amenities on property values in northwest Montana, USA. Ecological Economics, 69(11): 2233–2243.
22. Walls, M., Kousky, C., & Chu, Z. (2015). Is what you see what you get? The value of natural landscape views. Land Economics, 91 (1): 1–19.

A.2. Studies considered but not included

1. Bin, O., Landry, C. E., & Meyer, G. F. (2009). Riparian buffers and hedonic prices: a quasi-experimental analysis of residential property values in the Neuse River basin. American Journal of Agricultural Economics, 91(4): 1067–1079.
2. Coley, M. C. (2005). House and Landscape Value: An Application of Hedonic Pricing Technique Investigating Effects of Lawn Area on House Selling Price (Doctoral dissertation, University of Georgia).
3. Donovan, G. H., & Butry, D. T. (2010). Trees in the city: Valuing street trees in Portland, Oregon. Landscape and urban planning, 94 (2): 77–83.
4. Donovan, G. H., & Butry, D. T. (2011). The effect of urban trees on the rental price of single-family homes in Portland, Oregon. Urban Forestry & Urban Greening, 10(3): 163–168.
5. Hand, M. S., Thacher, J. A., McCollum, D. W., & Berrens, R. P. (2008). Intra-regional amenities, wages, and home prices: the role of forests in the Southwest. Land Economics, 84(4): 635–651.
6. Hjerpe, E., Kim, Y. S., & Dunn, L. (2016). Forest density preferences of homebuyers in the wildland-urban interface. Forest Policy and Economics, 70: 56–66.
7. Kim, Y. S., & Johnson, R. L. (2002). The impact of forests and forest management on neighboring property values. Society & Natural Resources, 15(10): 887–901.
8. Payton, S., Lindsey, G., Wilson, J., Ottensmann, J. R., & Man, J. (2008). Valuing the benefits of the urban forest: a spatial hedonic approach. Journal of Environmental Planning and Management, 51 (6): 717–736.
9. Snyder, Kilgore, Hudson, and Donnay. (2007). Determinants of Forest Land Prices in Northern Minnesota: A Hedonic Pricing Approach. Forest Science 53(1): 25–36.

References

Boyle, K.J., Wooldridge, J.M., 2018. Understanding error structures and exploiting panel data in meta-analytic benefit transfers. Environ. Resour. Econ. 69, 609–635.

Chicago Region Tree Initiative, 2018. Master Plan 2050 Executive Summary. Retrieved from. http://chicagorti.org/sites/chicagorti/files/Supplemental%20Attachment%20B.%2018CRTI_Master%20Plan-Executive%20Summary_FIN.pdf.

Cho, S.H., Lambert, D., Kim, S., Roberts, R., Park, W., 2011. Relationship between value of open space and distance from housing locations within a community. J. Geogr. Syst. 13, 393–414.

Coley, M.C., 2005. House and Landscape Value: An Application of Hedonic Pricing Technique Investigating Effects of Lawn Area on House Selling Price. Doctoral dissertation. University of Georgia.

Dimke, K.C., 2008. Valuation of Tree Canopy on Property Values of Six Communities in Cincinnati, Ohio. PhD Dissertation. The Ohio State University.

Donovan, G., Landry, S., Winter, C., 2019. Urban trees, house price, and redevelopment pressure in Tampa, Florida. Urban Forestry Urban Greening 38, 330–336.

Drake-McLaughlin, N., Netusil, N.R., 2010. Valuing walkability and vegetation in Portland, Oregon. In: von Haefen, R.H. (Ed.), Twenty-second Interim Report and Proceedings from the Annual Meeting, W2133, Benefits and Costs of Natural Resources Policies Affecting Public and Private Lands, pp. 173–201. https://fes.forestry.oregonstate.edu/sites/default/files/fes/pdfs/W2133%2022nd%20Interim%20Report%202010.pdf#page=173.

Dudley, T.E., 2012. The Value of Landscape Amenities: Contrasting Feature Proximity and View. MA Thesis. North Carolina State University.

Economics Research Service (ERS), 2013. Rural Urban Continuum Codes. United States Department of Agriculture, Washington DC. Retrieved from. https://www.ers.usda.gov/data-products/rural-urban-continuum-codes/.

Guignet, D., Jenkins, R., Ranson, M., Walsh, P., 2018. Contamination and incomplete information: bounding implicit prices using high-profile leaks. J. Environ. Econ. Manag. 88, 259–282.

Guignet, D., Heberling, M.T., Papenfus, M., Griot, O., Holland, B., 2020. Property Values, Water Quality, and Benefit Transfer: a Nationwide Meta-Analysis. Appalachian State University, Department of Economics (Working Paper Number 20-04. May, 2020).

Holmes, T.P., Murphy, E.A., Bell, K.P., 2006. Exotic forest insects and residential property values. Agricultural Resource Econ. Rev. 35, 155–166.

Holmes, T.P., Murphy, E.A., Bell, K.P., Royle, D.D., 2010. Property value impacts of hemlock woolly adelgid in residential forests. For. Sci. 56, 529–540.

Huggett Jr., R.J., 2003. Fire in theWildland-Urban Interface: An Examination of the Effects of Wildfire on Residential Property Markets. PhD Dissertation. North Carolina State University.

Johnston, R.J., Rosenberger, R.S., 2010. Methods, trends and controversies in contemporary benefit transfer. J. Econ. Surv. 24, 479–510.

Kadish, J., Netusil, N., 2012. Valuing vegetation in an urban watershed. Landsc. Urban Plan. 104, 59–65.

Kaul, S., Boyle, K., Kuminoff, N., Parmeter, C., Pope, J., 2013. What can we learn from benefit transfer errors? Evidence from 20 years of research on convergent validity. J. Environ. Econ. Manag. 66, 90–104.

Kiel, K.A., Williams, M., 2007. The impact of Superfund sites on local property values: are all sites the same? J. Urban Econ. 61, 170–192.

Kim, Y.S., Wells, A., 2005. The impact of forest density on property values. J. For. 103 (3), 146–151.

Klemick, H., Griffiths, C., Guignet, D., Walsh, P.J., 2018. Improving water quality in an iconic estuary: an internal meta-analysis of property value impacts around the Chesapeake Bay. Environ. Resour. Econ. 69, 265–292.

Li, X., Holmes, T., Boyle, K., Crocker, E., Nelson, C.D., 2019. Hedonic analysis of Forest Pest invasion: the case of emerald ash borer. Forests 10 (9), 820.

Lindhjem, H., Navrud, S., 2008. How reliable are meta-analyses for international benefit transfers? Ecol. Econ. 66, 425–435.

Mansfield, C., Pattanayak, S.K., McDow, W., McDonald, R., Halpin, P., 2005. Shades of green: measuring the value of urban forests in the housing market. J. For. Econ. 11 (3), 177–199.

Mazzotta, M.J., Besedin, E., Speers, A.E., 2014. A meta-analysis of hedonic studies to assess the property value effects of low impact development. Resources 3, 31–61.

McPherson, G.E., Xiao, Q., van Doorn, N.S., De Goede, J., Bjorkman, J., Hollander, A., Boiynton, R.M., Quinn, J.F., Thorn, J.H., 2017. The structure, function and value of urban forests in California communities. Urban Forests Urban Greening 28, 43–53.

Mei, Y., Hite, D., Sohngen, B., 2017. Demand for urban tree cover: a two-stage hedonic price analysis in California. Science 83, 29–35.

Nelson, J.P., 2015. Meta-analysis: statistical methods. In: Johnston, R., Rosenberger, R., et al. (Eds.), Benefit transfer of environmental and resources values. Springer, New York.

Nelson, J.P., Kennedy, P., 2009. The use (and abuse) of meta-analysis in environmental and natural resource economics: an assessment. Environ. Resour. Econ. 42, 345–377.

Netusil, N., Chattopadhyay, S., Kovacs, K., 2010. Estimating the demand for tree canopy: a second-stage hedonic price analysis in Portland, Oregon. Land Econ. 86, 281–293.

Newbold, S., Massey, M., Simpson, D., Heberling, M., Wheeler, W., Corona, J., Hewitt, J., 2018. Benefit transfer challenges: perspectives from U.S. practitioners. Environ. Resour. Econ. 69, 467–481.

Pataki, Diane E., Alberti, M., Cadenasso, M., Felson, A., McDonnell, M., Pincetl, S., Pouyat, R., Setälä, H., T.H., 2021. The benefits and limits of urban tree planting for environmental and human health. Front. Ecol. Evol. 9, 603757.

Paterson, R.W., Boyle, K.J., 2002. Out of sight, out of mind? Using GIS to incorporate visibility in hedonic property value models. Land Econ. 78 (3), 417–425.

Price, J.I., McCollum, D.W., Berrens, R.P., 2010. Insect infestation and residential property values: a hedonic analysis of the mountain pine beetle epidemic. Forest Policy Econ. 12 (6), 415–422.

Ready, R., Navrud, S., Day, B., Dubourg, R., Machado, F., Mourato, S., Spanninks, F., Vazquez-Rodriguez, M.J., 2004. Benefit transfer in Europe: how reliable are transfers between countries? Environ. Resour. Econ. 29, 67–82.

Rosenberger, R.S., 2015. Benefit transfer validity and reliability. In: Johnston, R., Rolfe, J., Rosenberger, R., Brouwer, R. (Eds.), Benefit Transfer of Environmental and Resource Values. Springer, Dordrecht, pp. 307–326.

Rosenberger, R.S., Phipps, T.T., 2007. Correspondence and convergence in benefit transfer accuracy: meta-analytic review of the literature. In: Navrud, S., Ready, R. (Eds.), Environmental Value Transfer: Issues and Methods. Springer, Dordrecht, pp. 23–43.

Sander, H., Haight, R.G., 2012. Estimating the economic value of cultural ecosystem services in an urbanizing area using hedonic pricing. J. Environ. Manag. 113, 194–205.

Sander, H.A., Polasky, S., Haight, R.G., 2010. The value of urban tree cover: a hedonic property price model in Ramsey and Dakota County, Minnesota, USA. Ecol. Econ. 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.

Siriwardena, S.D., Boyle, K.J., Holmes, T.P., Wiseman, P.E., 2016. The implicit value of tree cover in the U.S.: a meta-analysis of hedonic property value studies. Ecol. Econ. 128, 68–76.

Smith, V.K., Huang, J., 1995. Can markets value air quality? A Meta-analysis of hedonic property value models. J. Polit. Econ. 103 (1), 209–227.

Smith, V.K., Pattanayak, S., 2002. Is Meta-analysis a Noah's ark for non-market Valuation? Environ. Resour. Econ. 22, 271–296.

Stanley, T.D., Doucouliagos, H., 2012. Meta-Regression Analysis in Economics and Business. Routledge, New York, NY.

Stanley, T.D., Doucouliagos, H., Giles, M., Heckemeyer, J.H., Johnston, R.J., Laroche, P., Nelson, J.P., Paldam, M., Poot, J., Pugh, G., Rosenberger, R.S., 2013. Meta-analysis of economics research reporting guidelines. J. Econ. Surv. 27, 390–394.

Stetler, K.M., Venn, T.J., Calkin, D.E., 2010. The effects of wildfire and environmental amenities on property values in Northwest Montana, USA. Ecol. Econ. 69, 2233–2243.

U.S. Census Bureau, 2020. QuickFacts. Retrieved from: https://www.census.gov/quickfacts/fact/table/US/PST045219.

Vista, A.B., Rosenberger, R.S., 2013. Addressing dependency in the sportfishing valuation literature: implications for meta-regression analysis and benefit transfer. Ecol. Econ. 96, 181–189.

Walls, M., Kousky, C., Chu, Z., 2015. Is what you see what you get? The value of natural landscape view. Land Econ. 91 (1), 1–19.

Wooldridge, J.M., 2002. Econometric Analysis of Cross Section and Panel Data. The MIT Press, Cambridge, MA.