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Valuing public and private urban tree canopy cover*

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In this paper, we estimate the effect of tree canopy cover on sales price of urban residential properties in Perth, Western Australia. Using a data set of 5606 single family homes sold in 2009 and a spatial hedonic model with three spatial effects – spatial-temporal lag on dependent variable, spatial error, and spatially lagged independent variables – we estimated the location-specific effect of tree canopy cover. Tree canopy cover increases the property value when located on adjacent public space, but decreases the value when it is on own property and on the adjacent property within 20 m of property boundary. The results are suggestive that council urban tree planting programs provide significant private benefits to homeowners.

Key words: tree canopy cover, spatial hedonic model, spatiotemporal lag, property price, private space.

1. Introduction

Trees are one of the key urban amenities that provide a variety of benefits to urban residents. The range of such benefits vary from psychological to health improvement (Nielsen and Hansen 2007; Sugiyama *et al*. 2008; Donovan *et al*. 2011; Pereira *et al*. 2012), microclimate amelioration to reduced energy consumption (Dwyer *et al*. 1991; Simpson 1998; McPherson *et al*. 2005; Pandit and Laband 2010) and wildlife habitat (Dunster 1998) to carbon sequestration (Brack 2002; Escobedo *et al*. 2011).

Urban trees differ from other amenities that provide environmental benefits in urban areas, such as lakes or wetlands, as they are commonly located on both public and private spaces. Furthermore, from the perspective of a home owner, the distinction could be made between trees located on his/

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her own property and trees located on neighbouring properties. The location of trees affects access to the benefits they provide and the cost associated with these benefits, which may result in the residents valuing urban trees differently depending on tree locations. The owner has full access to the benefits trees provide when trees are located on the property, having full control over the planting and management, while incurring any management and opportunity costs associated with trees. An opportunity cost arises as trees compete with other uses of the limited space available on urban residential properties, such as house, garage or pool. When trees are located on spaces adjacent to the property, the owner neither has control over the management of the trees, nor incurs management or opportunity costs. Furthermore, the property owner can access the full benefits that trees located on adjacent public space provide, while the access to benefits provided by trees on adjacent private space remains limited.

Due to the public good nature of the benefits provided by trees, their value has commonly been estimated using nonmarket valuation techniques, particularly the hedonic pricing method (HPM) (Anderson and Cordell 1988; Tyrväinen and Miettinen 2000; Donovan and Butry 2010; Sander *et al.* 2010). There is a growing literature on the effect of type and mix of trees and green space on property value (Mansfield *et al.* 2005; Bark *et al.* 2009, 2011). A number of hedonic studies have looked at the value of trees on the property itself (Anderson and Cordell 1988; Dombrow *et al.* 2000), on the adjacent space (Donovan and Butry 2010) or both (Sander *et al.* 2010; Saphores and Li 2012; Pandit *et al.* 2013). However, using number of trees as a metric, only Donovan and Butry (2010) and Pandit *et al.* (2013) have thus far differentiated between the value of trees located on either public or private spaces. The shortcoming of this metric is that it does not account for a size effect of the tree, which can substantially influence the provision of environmental benefits. Most of the recent studies use either area of tree canopy cover (TCC) or proportion of tree canopy cover (PTCC), to capture the tree size effect on property values in accurately estimating the value of trees (Donovan and Butry 2010; Netusil *et al.* 2010; Sander *et al.* 2010).

In this paper, we use a spatial hedonic model to examine the value of trees measured by TCC, as differentiated by their location relative to the residential properties, in Perth metropolitan area of Western Australia. Specifically, we examine the value of TCC located on a property (own private space), on neighbouring properties (adjacent private space) and on the streets, parks and reserves adjacent to the property (adjacent public space). Understanding the location-specific value of TCC will help inform future urban forestry policies and management strategies in Perth and in other semi-arid metropolitan areas in Australia and worldwide.

From a modelling perspective, we have advanced environmental amenity valuation studies in two ways: (i) using empirical evidence, covariogram of Ordinary Least Squares (OLS) model residuals, in determining both cut-off distance and weights when constructing a spatial weight matrix; and (ii) by applying a general spatial model with spatiotemporal lag (Maddison 2009) to accommodate endogenous, exogenous and correlated spatial effects present in the data. This model is also referred to as a 'Manski model' (Elhorst 2010). Our point of departure from the Manski model is that the neighbouring house price is exogenous in our model to represent the spatiotemporally lagged effect of price, rather than any contemporaneous effect.

In the following sections, we present our study area, model and data. We then present and discuss the findings of the study based on aspatial and spatial models before concluding the paper with potential policy implications.

2. Study area

The study area covers the central part of the Perth metropolitan area in Western Australia, extending approximately 28 km north-south and 14.25 km east-west and covering a 398-km^2 area (Figure 1). It includes 14 city councils within the Perth metropolitan area, representing a range of socio-economic and developmental settings. The entire area is well-traversed by road networks. Amenities include Indian Ocean, Swan River and numerous parks.

The study area also captures the north-south and east-west variations in property prices and TCC within the central region of metropolitan Perth. For example, within the study area, the western suburbs (e.g. Mosman Park, Cottesloe, City Beach, Nedlands, Subiaco) have older and more expensive houses with mature tree scapes on both public space and private properties, while suburbs on the eastern, southern and northern borders of the study area (e.g. Karawara and Dianella) are relatively new with fewer large established trees on both streetscapes and private properties.

3. Model

The hedonic pricing method has been widely used to value individual attributes of a good based on its market price (Taylor 2003; Hanley and Barbier 2009). Rosen's (1974) utility theoretical framework and Lancaster's (1966) characteristic theory of value established the connection between consumer's preferences for house attributes and its equilibrium price. Thus, enabling the estimation of the marginal implicit price of individual attributes using the hedonic pricing model in housing markets, where it is assumed that the property price is made up of structural, locational and environmental attributes of the property.

Spatial data such as property sales are characterised by spatial dependence among observations and spatial heterogeneity (Anselin 1988), which implies that the hypothesis of the independence of spatial observations is an exception rather than a rule (LeSage and Pace 2009). Manski (1993) outlined three different types of spatial interaction effects: (i) endogenous interaction effect, that is, the effect of a dependent variable in other locations (neighbouring property price) on the behaviour or value of the dependent

Figure 1 Map of the study area with property locations.

variable in a given location (price of a given property), otherwise termed the spatial autocorrelation of the response; (ii) exogenous or contextual interaction effect, that is, the effect on a dependent variable in a location (price of a given property) comes from independent explanatory variables at other locations (property characteristics of neighbouring property), termed as spatially lagged effects of explanatory variables on the response; and (iii) correlated effect, that is, the interaction effect among the error terms – similar unobserved characteristics among observations result in similar effects (correlated errors).

Depending on the nature of spatial data, a combination of the above effects might exist and an appropriate spatial hedonic model is needed to estimate unbiased and robust parameters to draw valid inferences (Anselin 1988; LeSage and Pace 2009). Following Manski (1993), Elhorst (2010) formulated a general spatial model that incorporates all three types of spatial interaction effects which is referred to as the 'Manski model':

$$\begin{aligned} \mathbf{P} &= \rho\mathbf{WP} + \mathbf{X}\beta + \mathbf{WX}\theta + \mathbf{u}; \\ \mathbf{u} &= \lambda\mathbf{Wu} + \varepsilon \end{aligned} \tag{1}$$

where $\mathbf{P}$ is $N \times 1$ vector of home sale prices (dependent variable), ρ is the spatial autoregressive parameter (spatial lag), $\mathbf{W}$ is $N \times N$ spatial weight matrix, $\mathbf{X}$ is $N \times K$ matrix of exogenous explanatory variables, $\boldsymbol{\beta}$ is $K \times 1$ vector of parameter coefficients associated with explanatory variables, $\boldsymbol{\theta}$ is $K \times 1$ vector of parameter coefficients for lagged explanatory variables, $\mathbf{u}$ is $N \times 1$ vector of spatially correlated disturbance terms, λ is spatial autocorrelation (error) parameter, and $\boldsymbol{\varepsilon}$ is $N \times 1$ vector of independently and identically distributed error terms iid~(0, σ^2).

The vector of explanatory variables $\mathbf{X}$ represents three groups of property attributes (structural, locational and environmental) that can influence the sale price. Spatial weight matrix $\mathbf{W}$ defines the ways in which observations are believed to be affecting each other (see Anselin 1988; Taylor 2003; Conway *et al.* 2010 for details) and can be constructed in different ways depending on how we define the neighbourhood relationship between two observations: adjacency, k-nearest neighbours, inverse Euclidian distance and the length of common border, etc. (LeSage and Pace 2009; Corrado and Fingleton 2012). However, the choice of weight matrix should be guided by the research question and underlying data structure. In this study, we follow Polyakov *et al.* (2013) to identify an appropriate threshold-based spatial weight matrix, with both threshold distance and weights derived from the observed data, that is, by analysing residuals of the ordinary least squares hedonic model.

Furthermore, we use a different approach to construct a weight matrix to represent the spatial lag relationship for the response variable. The rationale for the existence of such a relationship in property sales data is that in making transaction decisions sellers and buyers are influenced by the prices paid for similar neighbouring properties. But these decisions are not influenced by the prices of properties that were sold a long time before or will be sold later than the property under consideration. We adopt the approach of Maddison (2009) and model the interaction effect of the dependent variable using spatiotemporal weight matrix $\mathbf{Z}$, which includes properties sold in earlier periods (90 days in our case) within the threshold distance for each property in the sample. At the same time, exogenous interaction effects and correlated effects are not determined by the time lag as they largely remain constant in value through time; therefore, we use spatial weight matrix $\mathbf{W}$ to represent these relationships. We call this model a 'Manski model with spatiotemporal lag':

$$\begin{aligned} \mathbf{P} &= \rho\mathbf{ZP} + \alpha\mathbf{I}_N + \mathbf{X}\beta + \mathbf{WX}\theta + \mathbf{u}; \\ \mathbf{u} &= \lambda\mathbf{Wu} + \varepsilon \end{aligned} \tag{2}$$

It has been argued that incorporating all three types of interaction effects into a single model is technically feasible, but the parameter estimates cannot be interpreted in a meaningful way since the endogenous and exogenous effects cannot be distinguished from each other (Manski 1993; Elhorst 2010). However, with the introduction of spatiotemporal weight matrix $\mathbf{Z}$, the lag effect becomes exogenous, which simplifies identification of the model (2). Elhorst (2010) suggests that a true model could be identified by setting a series of restrictions on the spatially lagged explanatory variables ($\boldsymbol{\theta} = 0$), spatially lagged disturbance terms ($\lambda = 0$), and spatially lagged-dependent variable ($\rho = 0$).

4. Data and Variables

We acquired property sales data for the year 2009 from Landgate, a state government agency that collects and distributes property data in Western Australia. From these data, we selected the sales records for single family homes only, resulting in 5606 observations for analysis. The data contained sale prices and structural characteristics of properties. The area of the house was missing in 80 per cent of the observations. We calculated the footprint area of the built structures on the property using a Digital Elevation Model acquired from the Western Australia Water Corporation (water.wa.gov.au; derived from discrete LiDAR captured at four points per m^2). We linked sales records with the cadastral map retrieved from Landgate's Shared Land Information Platform (SLIP: https://www2.landgate.wa.gov.au/) to delineate property boundaries and to create a spatial reference for each property. For the final analysis, we used 4200 properties that were sold in the last three quarters of 2009 out of 5606 observations in total. The spatiotemporal lag for each of these observations was constructed using properties within the threshold distance (1548 m) that were sold during 90 days prior to the sale of the property of interest.

To capture the potential effect of property shape on its value, we constructed and used a property shape index $\mathrm{PSI} = p/\sqrt{a}$ in the analysis where p is the property perimeter and a is the property area. It is expected that PSI is inversely related to the sales price to reflect the fact that, generally, between two otherwise identical properties a property with longer perimeter or smaller area costs less or *vice versa*.

Slope and elevation of the house location are important attributes that could impact the property value. We computed these attributes for each sample property using the Digital Elevation Model acquired from the Western Australia Water Corporation (water.wa.gov.au). The elevation in metres of the subject house was measured relative to the average elevation within a 1 km radius of that house, to capture whether the house is located in a valley or on a hill relative to its immediate surroundings.

Property prices in Australian cities are influenced by locational characteristics that include proximity to city centre, ocean and river (Tapsuwan *et al.* 2009; Hatton MacDonald *et al.* 2010; Pandit *et al.* 2013). To capture the influence of these locational characteristics, we calculated travel time to the Perth Business District (Perth Council House), the Indian Ocean and the Swan River following the designated road speed on motorways using Network Analyst for ArcGIS 10.0 (ESRI, Redlands, CA, USA). We believe that using driving time instead of driving distance or Cartesian distance may more realistically reflect the influences of these amenities on property value.

Data on the neighbourhood characteristics represented by the extent and location of recreational areas such as large parks, small neighbourhood reserves, lakes, sports reserves and golf courses were obtained from the GIS layer 'Metropolitan Region Scheme – Zones and Reservations' developed by the Department of Planning, Western Australia (available at SLIP portal). A gravity index of recreational areas within 3 km was constructed for each property following Powe *et al.* (1997). The gravity index captures the combined influence of their size and proximity on property value and can be expressed as:

$$\mathrm{GI}_{ri} = \sum\nolimits_{1}^{k} \frac{A_{rk}}{D_{ik}^{2}},$$

where GI_{ri} is the gravity index of k-th type of recreational area for i-th home in our sample, k is the number of 150×150 m grid cells within 3000 m radius of the i-th home, A_{rk} is the area of recreational site of r-th type within k-th grid and D_{ik} is the distance to the centre of the k-th grid from the i-th home.

To characterise individual suburbs and their potential effect on property value, we used suburb-specific data on burglaries and robberies for the year 2008 obtained from the Western Australian State Police Service (website http://www.police.wa.gov.au). We assume that the extent of crime (burglaries and robberies in this case) in a given year may have negative effect on property value in the following year(s).

The extent of TCC was extracted from remotely sensed data. We used distortion-corrected QuickBird standard-multispectral imagery of the study area taken on 10 January 2010, which has four multispectral bands at 0.5 m resolution. We classified the imagery into tree cover, grass, soil, water and impervious surface using Feature Analyst v. 5.0 for ArcGIS 10. The accuracy of the image classification was verified using 969 samples for both overall image classification and tree cover classification. The overall accuracy of the classification was 76.8 per cent, while the accuracy of TCC classification was 91.8 per cent.

The property boundary layer was superimposed over the TCC layer to derive PTCC within each property (private space). A 20-m buffer was created for each property boundary to calculate the PTCC on the streets, parks and reserves within the buffer area (adjacent public space) and on the neighbouring properties within the buffer area (adjacent private space). The average PTCC on the property was 24 per cent, while on the adjacent private space and on the adjacent public space, it was 26 per cent and 24 per cent, respectively. These figures were consistent with the PTCC in our study area. In 'urban' (mostly residential) land use, PTCC was 24 per cent, and within 20-m buffer of urban land use (mostly roads but also parks), it was 24.5 per cent. The descriptive statistics of variables in our sample (n = 4200) are presented in Table 1.

5. Results and discussion

The functional form for the hedonic model was derived from the data by applying a series of Box–Cox transformations, which resulted in a log-transformed dependent variable as the most appropriate form with zero value of transformation parameter. We also log-transformed all distance- and time-related variables as well as gravity indices. A square term for house age was also added in the model to examine potential nonlinear relationship between house age and property value because of any cultural or heritage values attached to older houses in our study context. We explored several models for PTCC variables: log-transformed (R^2 = 0.822), linear (R^2 = 0.824) and quadratic (R^2 = 0.825). While the quadratic model is marginally better than the linear, it does not change the substance of the overall results. We use model with linear specification of PTCC variables as the base case, but also present model results with quadratic specification.

The results of the OLS estimation of the hedonic model are presented in Table 2. Using OLS residuals, we calculated the empirical covariogram to design a spatial weight matrix (Figure 2). An empirical covariogram is a covariance between pairs of residuals depending on the distance (lag) between observations. The empirical covariogram was fitted with an exponential model $C(h) = s \times \exp(-h/r)$, with parameters '$h$' the distance (lag), 's' the 'scale' and 'r' the 'range' (Figure 2). The cut-off distance of the spatial weight matrix was selected at a point where the covariance falls to 5 per cent of its maximum value, which was at $h = 3 \times$ r. The parameter values of the fitted exponential covariogram were $s = 0.0202$ and $r = 516$; therefore, we constructed a row-standardised spatial weight matrix with a threshold distance of 1548 m based on the exponential decay function.

We tested OLS residuals for spatial autocorrelation using Moran's I and performed tests of spatial error and lag processes in the data using Lagrange

Table 1 Descriptive statistics of independent and dependent variables for hedonic analysis of housing prices in Perth (n = 4200)

Variables	Median	Mean	SD	Minimum	Maximum
Sale price (dependent variable)	800,000	1,007,051	806,177	104,855	11,910,000
Structural					
House age	43	43	26	1	141
Land area, m^2	705	677	229	145	3032
Property shape index	4.32	4.41	0.38	3.82	8.31
Footprint of built structures, m^2	284	294	95	98	958
Number of bathrooms	1.00	1.55	0.70	1	8
Number of bedrooms	3.00	3.20	0.89	1	6
Number of study rooms	0.00	0.24	0.43	0	3
Number of garages	1.00	0.90	0.89	0	7
Number of car ports	0.00	0.50	0.75	0	4
Swimming pool	0.00	0.24	0.43	0	1
Brick walls	1.00	0.86	0.35	0	1
Iron roof	0.00	0.15	0.35	0	1
Environmental					
Relative elevation, *m*	0.36	1.18	6.74	−19.67	37.19
Slope, degrees	1.96	2.35	1.74	0.01	14.69
PTCC on the property	0.22	0.24	0.16	0.00	0.83
PTCC on adjacent private space	0.25	0.26	0.13	0.00	0.77
PTCC on adjacent public space	0.20	0.24	0.17	0.00	0.98
Locational					
Drive time to the CBD, min	9.0	8.8	3.2	1.8	17.8
Drive time to the ocean, min	6.9	6.9	3.8	0.0	14.8
Drive time to the river, min	4.1	4.8	3.4	0.0	13.6
Distance to freeway, km	0.7	0.9	0.7	0.0	3.7
Distance to highway, km	2.9	3.5	2.4	0.0	9.5
Distance to bus stop, m	267	302	204	0	1563
Gravity index for small reserves	0.652	0.876	0.815	0.029	8.931
Gravity index for bush reserves	0.344	0.733	1.138	0.000	9.368
Gravity index for sports reserves	0.453	0.673	0.739	0.043	11.979
Gravity index for lakes	0.018	0.167	0.411	0.000	5.841
Gravity index for golf courses	0.180	0.374	0.719	0.000	9.428
Burglaries per 1000 houses	25.3	28.9	15.3	0.0	89.6
Robberies per 1000 population	0.6	0.9	1.3	0.0	14.0
Day of sale	235	231	77	92	365

PTCC, proportion of tree canopy cover.

multiplier and robust Lagrange multiplier tests (Anselin *et al.* 1996) (Table 3). The Moran's I statistic confirms the presence of spatial correlation in OLS residuals. The LM tests indicate the presence of both spatial lag and spatial error processes in the data.

We estimated the Manski model with spatiotemporal lag (spatial model). The model results are presented in Table 2. To test whether all three spatial effects belong to the model, we imposed restrictions on spatial parameters ρ, λ and $\boldsymbol{\theta}$. Likelihood ratio tests rejected the hypotheses that $\rho = 0$ ($\chi^2_1 = 258.4$, P-value = 2.20E-16), $\lambda = 0$ ($\chi^2_1 = 17.6$, $P <$ 2.77E-05), and $\boldsymbol{\theta} = 0$ ($\chi^2_{11} = 90.3$, P = 8.74E-13). Therefore, we concluded that model (2) was an appropriate model. In the rest of this section, we discuss the results of the estimation of

Table 2 Comparison of Parameter Estimates of OLS and Manski hedonic models (dependent variable is Log property price in 2009, AU$)

	OLS	Manski model with spatiotemporal lag	
	X	**X**	**WX**
Intercept	14.7700‡ (0.0770)	7.3184‡ (0.4342)	—
House age	−0.0088‡ (0.0007)	−0.0081‡ (0.0006)	0.0086† (0.0041)
House age^2	0.0001‡ (5.9E-06)	0.0001‡ (5.9E-06)	−0.0000 (3.8E-05)
Land area, m^2	0.0006‡ (2.4E-05)	0.0006‡ (2.4E-05)	−0.0002 (0.0001)
Property shape index	−0.0609‡ (0.0103)	−0.0391‡ (0.0096)	0.1677† (0.0666)
Footprint of built structures, m^2	0.0004‡ (0.0001)	0.0004‡ (0.0001)	−0.0004 (0.0004)
Number of bathrooms	0.1205‡ (0.0079)	0.1043‡ (0.0073)	−0.0413 (0.0574)
Number of bedrooms	0.0265‡ (0.0057)	0.0212‡ (0.0052)	0.0882† (0.0421)
Number of study rooms	0.0769‡ (0.0096)	0.0567‡ (0.0089)	−0.0294 (0.0782)
Number of garages	0.0496‡ (0.0060)	0.0435‡ (0.0055)	0.0812* (0.0419)
Number of car ports	0.0098 (0.0064)	0.0039 (0.0058)	0.1086† (0.0494)
Swimming pool	0.0854‡ (0.0093)	0.0738‡ (0.0085)	0.0282 (0.0731)
Brick walls	0.0461‡ (0.0122)	0.0258† (0.0114)	−0.1160† (0.0539)
Iron roof	0.0488‡ (0.0122)	0.0398‡ (0.0112)	−0.0275 (0.0741)
Relative elevation, m	0.0042‡ (0.0006)	0.0027‡ (0.0006)	−0.0075‡ (0.0024)
Slope, degrees	0.0081‡ (0.0022)	0.0078‡ (0.0020)	−0.0127 (0.0093)
PTCC on the property	0.0556* (0.0308)	0.0305 (0.0284)	—
PTCC on adjacent private space	0.0007 (0.0352)	−0.0762† (0.0328)	—
PTCC on adjacent public space	0.3026‡ (0.0260)	0.1814‡ (0.0246)	—
Log (drive time to the CBD)	−0.5362‡ (0.0152)	−0.2583‡ (0.0278)	—
Log (drive time to the ocean)	−0.2977‡ (0.0061)	−0.1745‡ (0.0094)	—
Log (drive time to the river)	−0.1758‡ (0.0042)	−0.1110‡ (0.0061)	—
Log (distance to freeway)	0.0609‡ (0.0051)	0.0258‡ (0.0069)	—
Log (distance to highway)	0.0513‡ (0.0038)	0.0371‡ (0.0038)	—
Log (distance to bus stop)	0.0256‡ (0.0039)	0.0222‡ (0.0036)	—
Log (gravity index for small reserves)	−0.0396‡ (0.0128)	0.0130 (0.0126)	—
Log (gravity index for bush reserves)	0.0440‡ (0.0093)	0.0480‡ (0.0113)	—
Log (gravity index for sports reserves)	0.0030 (0.0121)	−0.0067 (0.0116)	—
Log (gravity index for lakes)	0.0972‡ (0.0192)	0.0438† (0.0221)	—
Log (gravity index for golf courses)	0.0549‡ (0.0117)	0.0306† (0.0131)	—
Burglaries per 1000 houses	−0.0029‡ (0.0003)	−0.0011‡ (0.0004)	—
Robberies per 1000 population	−0.0105‡ (0.0033)	−0.0042 (0.0034)	—
Spatiotemporal lag	—	0.4147‡ (0.0226)	—
Spatial error	—	0.3987‡ (0.0621)	—
N	4200	4200	—
R^2	0.824	—	—
Adjusted R^2	0.822	—	—
Log Likelihood	254.0	606.6	—
AIC	−427.9	−1097.2	—

Note: Standard errors are in parentheses. Months dummy variables are not included. *Significant at 10 per cent level; †significant at 5 per cent level; ‡significant at 1 per cent level. PTCC, proportion of tree canopy cover.

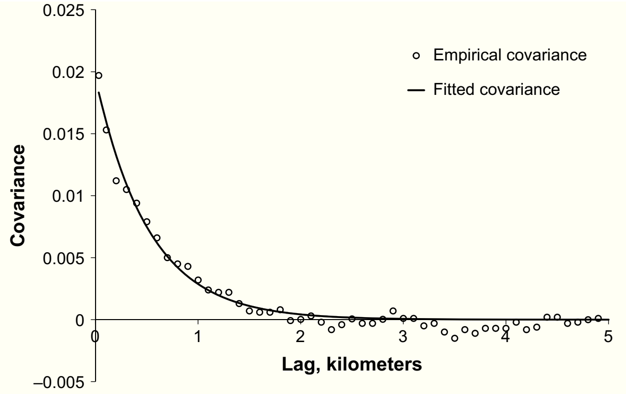

Figure 2 Covariogram of the residuals from the OLS estimation of the hedonic model.

Table 3 Tests for spatial autocorrelation in the OLS model based on distance based spatial weight matrix

Test	Test value	*P*-value
Spatial correlation in OLS residuals		
Moran's I statistics standard deviate	23.3	<2.2e-16
Spatial error dependence		
Lagrange multiplier test	527.0	<2.2e-16
Robust Lagrange multiplier test	382.7	<2.2e-16
Spatial lag dependence		
Lagrange multiplier test	307.5	<2.2e-16
Robust Lagrange multiplier test	163.2	<2.2e-16
Spatial lag and error dependence (SARMA)		
Lagrange multiplier test	690.2	<2.2e-16

the Manski model with spatiotemporal lag and compare these results with the OLS model results.

As anticipated, all structural attributes of the property have significant influences on property price in both OLS and spatial models. The magnitude of some coefficients was smaller in the spatial model suggesting that there is a bias in parameter estimation if spatial effects were not taken into account. House age had a quadratic relationship with property price that suggests a decrease in house price each year up until 62 years of age when price starts increasing. Land area had a highly significant positive impact on property prices. The property shape index had a significantly negative impact on property price, suggesting that everything else being equal, a property with longer perimeter has a lower price.

The majority of locational variables also exhibit consistent and significant impacts on property price in both models. For example, driving time to the Indian Ocean and the Swan River have negative and statistically significant impacts on property price, suggesting that a property close to the Indian

Ocean or the Swan River carries higher premium compared to otherwise similar properties located further away from these features. A one per cent increase in driving time to the Indian Ocean or the Swan River decreases the property price by about 0.17 per cent and 0.11 per cent, respectively. Similarly, a one per cent increase in driving time to Perth CBD increases property value by 0.25 per cent. We expected that proximity to the freeway and highway to be disamenities for residents and found that their proximities do have negative effects on property prices. The results further indicate that proximity to a bus stop was a disamenity and the property price increased by 0.02 per cent for one per cent increase in average distance (9 m) from the bus stop.

Bush reserves, lakes and golf courses had significant and positive impacts on property price. But the results do not support a statistically significant effect of small and sports reserves on property prices. Among the location features, a house located on a steeper slope or at a higher elevation relative to its surrounding had a higher value compared to an otherwise identical house. Crime statistics represented by burglaries per 1000 houses in the previous year had a significant negative influence on property price in the following year; however, we did not find a similar effect of robbery statistics on property price.

The PTCC on and around the property had a mixed effect on property price. We expected that the PTCC on own property, on the adjacent private space and on the adjacent public space would have a positive influence on property price. But we found that the PTCC on own property did not have a significant effect on the property price, while PTCC on the adjacent private space had significant negative effect when spatial effects were taken into account. The reasons for a negative price effect of PTCC on the adjacent private space could include tree-related aesthetic and safety concerns such as blocking view and light, dropping leaves and twigs, poor condition of trees, potential for structural damage and causes of dispute between neighbours. On the other hand, the PTCC on the adjacent public space had a significant and positive impact on property price in both OLS and spatial models. However, the magnitude of the coefficient in the spatial model was substantially smaller than in the OLS model, indicating overestimation of the effect of PTCC on adjacent public space when spatial effects were not taken into account.

Table 4 presents spatial model estimates with alternative specifications for PTCC. In the aggregated models, PTCC was calculated on the property and 20-m buffer without differentiating the space into private and public. In the aggregated model with linear specification, PTCC on adjacent public space had a significant positive effect, similar in magnitude to the effect of PTCC in the base case model. The linear and quadratic terms were jointly statistically significant at 1 per cent confidence level. While the quadratic term was significant, it was of low magnitude and did not deviate substantially from the linear trend (Figure 3). In the disaggregated models, the PTCC term for own

Table 4 Comparison of linear and quadratic specifications for PTCC in Manski model with spatiotemporal lag

Variables	Aggregated TCC		Disaggregated TCC	
	Linear	Quadratic	Linear	Quadratic
PTCC on the property and within 20-m buffer	0.2053‡ (0.0307)	0.0048 (0.0856)	—	—
PTCC on the property and 20-m buffer squared	—	0.3503† (0.1396)	—	—
PTCC on the property	—	—	0.0305 (0.0284)	−0.0248 (0.0706)
PTCC on the property squared	—	—	—	0.1028 (0.1102)
PTCC on adjacent private space	—	—	−0.0762† (0.0328)	−0.3408‡ (0.0986)
PTCC on adjacent private space squared	—	—	—	0.4632‡ (0.1589)
PTCC on adjacent public space	—	—	0.1814‡ (0.0246)	0.0720 (0.0642)
PTCC on adjacent public space squared	—	—	—	0.1766* (0.0946)
AIC	−1088.1	−1092.4	−1097.2	−1107.7

Notes: Standard errors are in parentheses. Months dummy variables are not included. *Significant at 10 per cent level; †significant at 5 per cent level; ‡significant at 1 per cent level. TTC, tree canopy cover; PTCC, proportion of tree canopy cover.

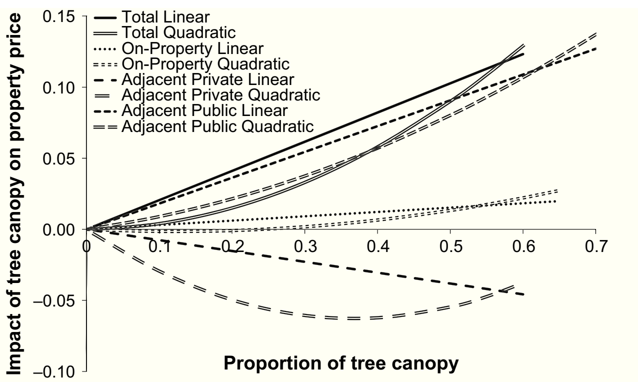

Figure 3 Impact of the tree canopy on property price as a function of the PTCC.

property was not statistically significant neither in the linear nor in the quadratic specification of the model. Similar to the aggregated model, the quadratic term for the effect of PTCC on the adjacent public space was statistically significant at 1 per cent level, but of low magnitude. Contrary to our expectations, we did not find a diminishing marginal benefit of the PTCC on adjacent public space. In contrast, the term for PTCC on adjacent private space was statistically significant. The effect was substantial, ‘U’-shaped and negative within the range of this variable, achieving a maximum when PTCC on the adjacent private space reached 37 per cent, which was approximately the third quartile value of this variable in our sample. This result indicates a diminishing marginal disamenity in the effect of PTCC on adjacent private space. It is likely that the disamenity effect of PTCC on adjacent private space often arises from trees located along the property boundary. Any increase in PTCC on the adjacent property would then be associated with trees located farther away from the boundary or from trees in the interior part of the adjacent property in which case additional PTCC may have different property price effects.

In Table 5, we report the marginal implicit price of significant variables based on spatial model results. When evaluated at the median property price (AU$ 800,000) and median PTCC on public space (20 per cent), the implicit price of a 10 per cent increase in TCC was about AU$14,500 (approximately 1.8 per cent of the median property price). On the other hand, an increase in TCC on the adjacent private space by 10 per cent reduced the property price by about AU$ 6100. Based on the OLS model, which does not control for spatial effects, the implicit price of a 10 per cent increase in TCC on the adjacent public space was estimated at AU$ 24,200,

Table 5 Marginal implicit price (MIP) for significant variables based on Manski model (median house sale price AU$ 800,000)

Variables	MIP (AU$)
House age*	−1956
Land area, m^2	474
Property shape index	−31,304
Footprint of built structures, m^2	300
Number of bathrooms	83,456
Number of bedrooms	16,936
Number of study rooms	45,327
Number of garages	34,792
Swimming pool	59,027
Brick walls	20,653
Iron roof	31,858
Relative elevation, m	2182
Slope, degree	6236
Per 10% TCC on neighbouring private space	−6099
Per 10% TCC on adjacent public space	14,510
Drive time to the CBD, min	−22,941
Drive time to the ocean, min	−20,231
Drive time to the river, min	−21,841
Distance to freeway, km	29,924
Distance to highway, km	10,180
Distance to bus stop, m	66
Gravity index for bush reserves	111,655
Gravity index for lakes	1,969,569
Gravity index for golf courses	135,798
Burglaries per 1000 houses	−908

Note: *The MIP for house age is based on median age (43 years). The sales price is nonlinearly related to house age with the threshold age of 62 years. TTC, tree canopy cover.

while the effects of TCC on adjacent private space was not statistically significant.

The finding of the positive property price effect of PTCC on street verge (public space) is broadly consistent with earlier studies (Donovan and Butry 2010; Sander *et al*. 2010; Saphores and Li 2012). Donovan and Butry (2010) found a positive impact of the number of street trees and tree cover within 30.5 m on home sales price in Portland, Oregon. In a Minnesota-based study, Sander *et al*. (2010) reported that a 10 per cent increase in tree cover (from 14.55 per cent to 24.55 per cent) within a 100-m buffer of the property boundary increased average property price (US\$ 287,637 in 2005) by US\$ 1371 (0.48 per cent). Saphores and Li (2012) found that increase in tree cover in nearby areas, in both private and public spaces, benefited most properties. However, neither of these studies differentiated TCC around the property into TCC on private and public space. Therefore, the findings of these studies represent the combined effect of TCC on the adjacent private and public spaces. However, Pandit *et al*. (2013) did make such a differentiation and did not find a significant effect of trees located on the adjacent private space on property price, but they found that broad-leaved trees on the street verges (adjacent public space) had a significant property price effect.

The work by Saphores and Li (2012) is comparable to our study in terms of similar Mediterranean climate and a metropolitan area with relatively high property prices. For instance, the mean price of an average house in Los Angeles and in Perth was about US\$ 526,830 (i.e. US\$ 735.80 m^{-2}) in 2003/04 and AU\$ 1,006,326 (i.e. AU\$ 1497 m^{-2}) in 2009, respectively. In contrast, the mean property price in Minnesota (Sander *et al*. 2010) was US \$ 287,636 (US\$ 209 m^{-2}), and the median price in Portland (Donovan *et al*. 2011) was US\$ 259,000 (US\$ 478 m^{-2}). Despite the different study periods, the per unit price difference among these studies indicate different opportunity cost of space available for trees in residential lots. The opportunity cost of space on a residential property was relatively high in Perth and Los Angeles where we find negative or small positive effects of increased TCC on the own private space on property price. On the other hand, the opportunity cost of private space in Minnesota and Portland studies were low where the effect of additional trees or green cover had positive impacts on property price. Thus whether a tree or tree cover on private property has positive or negative effects on property price partly depends on the opportunity costs of the private space. We believe that not finding a statistically significant positive price effect of the PTCC on the property in Perth reflects the high value of private space in residential properties.

6. Conclusions

This study examines the location-specific value of TCC captured by property prices in the central region of the Perth metropolitan area using a spatial hedonic model. On average, a 10 per cent increase in TCC on the adjacent public space adds a property price premium of about AU$ 14,500, while the same proportional increase in TCC on adjacent private property reduces the property price by AU$ 6100. We did not find diminishing marginal benefits of PTCC on adjacent public space, but we found a diminishing marginal disamenity of PTCC on adjacent private space. Further, we find that parameter estimates for PTCC on public space and adjacent private space are significantly different between the OLS and spatial models.

These location-specific effects of PTCC on property prices have potential impacts on urban forestry programs in the Perth metropolitan area. All Perth city councils have street tree management guidelines in place that describe the detailed procedures on street tree plantation, management and removals including species selection. Older city councils, for example, Town of Claremont, have street tree replacement programs for damaged, postmature and stressed trees. Other city councils, for example City of Stirling, have street tree planting programs for newly developed suburbs. We suggest that in street tree planting considerations should be given to the economic value of street trees to the property owner and trees with larger canopy covers should be introduced in line with the council's protocol on species selection.

Not finding a statistically significant positive property price effect of tree covers on the property may reflect the costs associated with managing trees as well as the opportunity costs. There could be disamenities associated with tree cover on private space, such as blocking views, dropping leaves and damage to pavement (Donovan and Butry 2010). In addition, large trees can damage other infrastructure (e.g. falling branches in storms) and occupy valuable private space that could be used for other purposes. TCC on private space incurs private costs, while TCC on street verges provides benefits without incurring significant private costs, that is, space to grow trees and costs to manage them. Clearly, from a societal perspective, developing or maintaining TCC on street verges provides residents with some private benefits, but without many direct costs.

This study indicates that maintaining or developing forest cover around suburbs also provides private benefits and in turn higher property prices, which through council rates or taxes to property owners can be used to support urban tree programs. The study findings are applicable to other Australian cities and other semi-arid metropolitan areas worldwide. However, what perceptions residents hold on trees or tree cover on private space is unclear and cannot be inferred from this study. Future studies on urban forestry in Australian cities and in other parts of the world should focus on residents' perceptions and behavioural attitudes towards trees and tree cover on residential properties that could provide useful insights to city authorities and urban planners to develop and maintain urban greenery.

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