Measuring the Amenity Value of Urban Open Space Using a Spatial Hedonic Approach: the case of Edmonton, Canada

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Highlights

- Attributes affecting house prices have positive spatial spillovers on prices of neighbouring houses.
- People's WTP for permanent open spaces are higher than for developable land.
- WTP for land conservation varies by the functionality associated with different types of open space.
- Proximity to forests, parks and a university farm have significant positive effects on house prices.
- Proximity to farmland has significant negative effect on house prices.

Abstract

To optimize land conservation strategies with limited resources and funds, it is necessary to understand people's preferences and willingness to pay (WTP) for different types of open space. The hedonic pricing method (HPM) is widely used in the literature. However, the conventional econometric approach of investigating HPM often assumes that the values of open space do not affect property values in the neighboring areas, which might be violated in reality because of externalities and spillovers. We adopt a spatial regression approach and relax the no-spillover assumption. Through an analysis of the impacts of different types of open space on house prices in Edmonton, Canada, we illustrate how the spatial HPM can be used to quantify open space values including both own and spillover values. The results show that people are willing to pay a premium for access to forest land, shrubland, and woodland. However, the WTP for residing close to farmland is negative. One possible explanation of the different WTP is the heterogeneous functions (thus values) and the potential for future land development associated with different types of open space. Furthermore, our study indicates that the WTP for open space has significant spillover effects. Ignoring such spillovers can lead to underestimating the total value of open space protection and, thus, the optimal amount of land conservation.

Key Words: urban open space; hedonic pricing method; spillovers; spatial econometrics; marginal willingness to pay; housing price

Introduction

Urban open space provides a wide range of benefits to people including psychological relexation and reduced exposure to pollutants, noise and heat (Braubach et al., 2017). Open space is also an important factor in balancing ecosystem function and sustainable development (Irwin, 2002; Anderson and West, 2006; Enssle and Kabisch, 2020). With continuous economic development, population growth, and accelerated urbanization, more and more open space has been or is under pressure to be developed. The public natue of the benefits of open space create gaps between private and social optimal supply and demand of land for development and conservation. To correct such market failures, governments inevitably play crucial roles in protecting remaining open space. In the past several decades, governments at all levels around the world have taken various steps to conserve open space (Boulton et al., 2018).

To optimize land conservation strategies with limited resources and funds, it is necessary to evaluate the value of different types of open space. These value estimates facilitate governments to conduct benefit/cost analysis and predict the consequences of possible policies. For example, a government considering an urban green belt would benefit from knowing the premiums that homeowners may be willing to pay to live near the green belt. A price premium would increase the government's fiscal revenue from property tax.

The literature on people's willingness to pay (WTP) for urban and peri-urban open space mainly uses two methods: stated preference and revealed preference (Bergstrom and Ready, 2008), with the latter being the majority. Revealed preference studies often use the hedonic pricing method (HPM) to estimate the implicit price of (and thus, people's WTP for) open space through analysis of the real estate market. Many existing studies focus on a specific type of open space, such as parks (Trojanek et al., 2018; Laszkiewicz et al., 2019), farmland (Johnston et al., 2001; Ready and Abdalla, 2005), or urban greeneries (Du and Huang, 2018). Some research also includes several different types of open spaces and compare the WTP associated with each type (Geoghehan, 2002; Anderson and West, 2006; Bowman et al., 2012; Cao et al., 2021). Furthermore, some research suggests that people's WTP varies greatly depending on whether it is a permanent or a temporary/developable open space (Irwin, 2002; Crompton and Nicholl, 2020). We expect people's WTP for permanent open spaces such as urban built parks to be higher than for developable land such as peri-urban private farmland (Irwin and Boackstael, 2001; Geoghehan, 2002; Crompton and Nicholl, 2020). Empirical research should distinguish between permanent and developable open spaces.

Build upon the existing literature, we propose that the value of open space and people's WTP should be distinguished not only by the permanent/temporary distinction but also by the heterogeneous functions/values of open space from both societal and ecological perspectives. The main functions of open space include productive (e.g., agriculture and forestry), aesthetic and recreational / athletic, and ecological (e.g., biodiversity, regulating microclimate, climate cooling). Distinguishing WTP by function can explain some common dilemmas that may not be explained by existing frameworks. For example, people's WTP for urban developable forests is often larger than permanent open space such as built parks and playgrounds (Crompton and Nicholl, 2020).

Similarly, people's WTP for urban forests, especially large-scale national/city parks with various functions, such as the Stanley Park in Vancouver, will be much larger than that for private farms located in urban boundary areas. However, they are frequently classified together as non-permanent/developable land. Although physically developable, such large-scale urban reserved green spaces are usually unlikely to be developed. Therefore, it is not appropriate to simply divide open space into permanent or developable; the probability of development and their functionalities need to be considered.

One more complication should be considered in studies of the value of open space: spatial correlation of housing prices. High-value houses and low-value houses are often clustered in specific communities in a city. The underlying reasons behind the spatial correlation of housing prices are social segregation, income distribution, and neighborhood choice/sorting (Musterd, 2016; Owens, 2019). Earlier studies of WTP often ignored spatial autocorrelation (Macdonald and Veeman, 1996; Islam, 2012), leading to bias in the estimation results. Recent research has begun to use spatial regression models to control for spatial interactions (Cao et al., 2021; Yoo et al., 2017; Kim et al., 2020). In addition to reducing bias, using spatial regression models can also directly quantify spillover effects caused by spatial/neighbor interactions.

Improving open space access for one house is likely to affect the prices of nearby houses (Sohn et al., 2020). Although some of the existing literature uses spatial HPM, few have quantified the spillover effects, which could be essential for accurately estimating the benefits and costs of land conservation. Ignoring the positive WTP of neighbors can lead to underestimating the total value of land protection and, thus, the optimal amount of protection.

Therefore, the objective of this article is to use spatial HPM to study people's WTP for different types of open space. Our contribution is mainly twofold. First, we specifically quantify spillover WTP from neighbors, making WTP/value estimation more accurate. Second, we distinguish open space with regards to its functions and the possibility for future development. In the empirical study of the City of Edmonton, Canada we group open space into four categories: permanent built-up open space (such as community and city parks), agricultural land, urban forests and greeneries, and the University of Alberta farmland. There are many differences between the university farm and other private farms. For example, university farms have educational and research functions, which other private farms do not have. Moreover, the size of the university farm is much larger than that of other private farms within the city. Therefore, it is reasonable to expect that the premium for living near the university farm to be significantly different from the premium (if any) associated with proximity to other private farms.

2. Data and variables

2.1 Study area

The study area of this analysis is the City of Edmonton. It is the capital city of the Canadian province of Alberta, located on the North Saskatchewan River and is the heart of Edmonton Metropolitan Area. From 2011 to 2016, Edmonton's population grew by 14.8% (812,201 in 2011 and 932,546 in 2016), which made it the second largest city in Alberta and the fifth most populous urban municipality in Canada (Statistics Canada, 2017). After annexations of parts of five adjacent urban municipalities (Strathcona, North Edmonton, West Edmonton, Beverly, and Jasper Place) that doubled the surface area of Edmonton in the 1980s, Edmonton annexed another 8,260 hectares of land from Leduc County and the City of Beaumont in 2019 (City of Edmonton, 2018). The City of Edmonton maintains 4,600 hectares of grassland and contains more than 460 parks. Besides the grassland, the North Saskatchewan River Valley and ravine system forms a "Ribbon of Green" that provides opportunities for walking, jogging, bike riding, picnicking, snowshoeing and cross-country skiing. This includes more than 22 major parks and 150 kilometers of maintained pathways (City of Edmonton, 2017). Using 2016 land coverage data from the Agricultural and Agri-food Canada (AAFC) Annual Crop Inventory website (Government of Canada, 2020), we estimate that 35% of the City of Edmonton is covered by open space with approximately 12,446 hectares in agricultural uses, 2,861 hectares as woodlands and 9,276 hectares in parks, rivers and wetlands.

Projected to increase population from 1.2 million to 2.1 million people by 2050 (City of Edmonton, 2019), the conversion of land is unavoidable to fufill growing needs for housing, light industry and commercial uses. In response to urban growth, the city implements various strategies to guide the conservation of open space: The Way Ahead, The Way We Grow, and The Way We Green. The Way We Green was recently transformed to the most recent strategy "BREATHE" to ensure the sustainability of the neighbourhoods by supporting a network of open space at the site, neighbourhood, city and regional levels (City of Edmonton, 2017).

2.2 Data

The housing price used in this study is the real transaction price provided by Real Property Solutions (RPS), which is a leading national resource for housing data and was shown to cover 70% of all recorded housing transaction in a study by Yeates et al. (2012). The housing transaction information is filtered by some criteria. To enhance comparability of housing prices, only single-family detached houses are selected. This type of housing compromises 80% of the houses sold in Edmonton real estate market (Zolo, 2020). A time period with no major fluctuation in the housing market (Tenant and National Bank of

Canada, 2020) was selected and data pooled for January 2015 to June 2017. After excluding some missing values and keeping only one transaction for houses that had recorded more than one transaction during the study period, a sample size of 9495 observations was reached. The House Price Index (HPI) (The Canadian Real Estate Association) for Edmonton was used to adjust all property values to constant 2016 Canadian dollars.

2.3 Variables

The variables are described in Table 1 with their mean values and units. The structural variables are available in the dataset provided by Real Property Solutions, including living area, lot size, year sold, number of bathrooms, number of bedrooms, condition of house, condition of basement and number of parking spaces. The season when the house is sold is added because the value of the house tends to be higher if sold between April and September.

Measures of the distance to the city core and the nearest Light Rail Transit (LRT) station were included. Distance-based variables were generated by analyzing geographic coordinates using the proximity tool in the ArcGIS software. Distance to downtown Edmonton is included since the Provincial legislature, City administration, and financial and engineering service sectors are all centered in the downtown core. Proximity to Light Rain Transit (LRT) stations reduce transit times and have exerted upward pressure on the prices of nearby houses in other studies (Dziauddin et al., 2015; Hui et al., 2007).

House prices are often found to be affected by neighbourhood characteristics. This study uses 2016 census information for the neighbourhood[1] in which the property is located (Open Alberta; City of Edmonton). Population density is included, as higher density residential areas may be associated with negative congestion externalities such as high traffic volume and noise. The percentages of youth and elderly people define the dynamics of a neighbourhood and often the maturity of the housing market. Edmonton has experienced rapid growth over the last 50 years, often with younger families moving into newer developments near the edge of the city. Highly-educated households with children may have higher demand for environmental quality, which in turn, may put upward pressure on house prices (Brasington and Hite, 2003; Sedgley et al.,2008). Previous studies indicate that neighbourhoods with more university-educated individuals generally have higher house prices (Borchers and Duke, 2012). Elementary school quality [2] and crime incidence (Dubin and Goodman, 1982) are also considered to be important neighbourhood characteristics. Percentage of residents with low income, percentage of residents with high income, and unemployment rate are included as indicators of the relative economic position of a neighbourhood (Downs, 2002). Possible regional clustering of high and low-priced houses is controlled by a regional dummy for neighbourhoolds in which the average property value is higher than the average for all neighbourhoods.

Crop inventory data[3] provided by Agriculture and Agrifood Canada (AAFC) were used to construct the environmental variables in the ArcGIS software. Land-use types from the AAFC crop inventory data and land designation data from the City of Edmonton were aggregated into four categories: developable agricultural land[4], developable woodland[5], non-developable land[6], and the University of Alberta South Campus, which is the main area of contiguous agricultural land near the centre of the City of Edmonton. University of Alberta South Campus is unique because it is primarily used for agricultural experiments, but could be further developed if the built infrastructure of the university continues to expand.

Non-developable land is a land use designation that does not account for whether or not the municipality has designated the land for a developed use. The coarse granularity of the land use data means that this analysis focuses on large-scale land uses, although there also is small-scale urban agriculture such as community gardens and urban farms within the core of the city. There is some overlap between non-developable land and agricultural land in the middle of the city along the river valley, including a horse riding facility. We prioritize non-developable land so that the land polygons of agricultural land are removed if they overlap with non-developable land.

The effect of recent development was accommodated by the inclusion of a land use change variable that measures the acres of land that changed from agricultural to developed within a particular buffer of the property over the six years prior to the house sale, for example 2009-2015 for houses sold in 2015 and 2010 to 2016 for houses sold in 2016. The effects of recent change in land use on housing prices are less well studied than other house attribues (Acharya and Bennett, 2001). We thus had no priors about the geographic spillover of this land use change effect. After trying buffers with radii of 100m, 200m, 500m, 1km and 2km, the 1km buffer produced the results with the highest statistical significance level.

Table 1. Definition of Variables and Sources Included in Hedonic Price Model

Variables	Definition	Units	Mean
Dependent variable	Adjusted House Transaction price from 2015 to 2017	$ (2016$)	454,736
Structural Variables			
Living area	Square feet of living space	Square feet	1,569
Lot size	Square feet of lot size	Square feet	5,838
Age	Age of the house	Years	29
Bath	Number of full bathrooms	Count	1.65
Bed	Number of full bedrooms	Count	2.92
Condition	1 if condition is "excellent" or "good", 0 otherwise	0, 1	0.52
Basement	1 if basement is "finished", 0 otherwise	0, 1	0.66
Parking	Number of parking spaces	Count	1.78
Season	1 if the house is sold between April and September, 0 otherwise	0, 1	0.51
Locational Variables			
Downtown	Distance to downtown	Km	7.66
LRT	Distance to nearest LRT station	Km	4.57
Neighbourhood Variables			
Density	Population/acres of developed land in neighbourhood	Individual/acres	3,001
Child	Percentage of population aged 5 to 19 years old	Percent	17.4
Elder	Percentage of population aged over 60	Percent	19.33
Unemployment	Unemployment rate in 2016	Percent	5.14
Low Income	Percentage of people with income less than $30,000	Percent	12.14
High Income	Percentage of people with income more than $150.000	Percent	17.25
Bachelor	Percentage of people with at least get bachelor’s degree	Percent	32.06
Crime Incidence	Number of crime events in each neighbourhood in 2016	Count	27.06

Quality	Score of designated public elementary school (0-10)	0-10	5.97
Regional Factor	Dummy variable that equals 1 if average house price in the neighbourhood is higher than sample mean, 0 otherwise	0, 1	0.39
Environmental Variables			
Agricultural	Distance to nearest developable agricultural land	km	2.54
Woodland	Distance to nearest developable woodland	km	0.33
Non-developable	Distance to nearest non-developable land	km	0.17
UA farm	Distance to University of Alberta Farm	km	7.93
Land-use change	Acres of recent six-year land-use change within 1km buffer	Acres	69.72

3. Models

3.1 Hedonic Pricing Method

The hedonic pricing method, based on the theoretical framework introduced by Rosen (1974), is a revealed preference technique that assumes that purchasers of a good are purchasing a collection of attributes of that good. Underlying the hedonic framework is a theory of consumer behavior that assumes that goods are valued based on their individual “utility bearing” attributes or characteristics (Rosen 1974). Following this, house prices are a function of their various attributes:

$$P=(\mathrm{S, L, N, E}, \varepsilon) \quad (1)$$

where P is a vector of housing prices; S, L, N, E are vectors of structural attributes, locational attributes, neighbourhood attributes and environmental attributes respectively; ε is a vector of error terms that capture the effects of all unobserved variables. The partial derivative of the price function with respect to an explanatory variable j is the marginal willingness to pay for that attribute, also called the implicit price of that attribute. It is worth noticing that this version of the hedonic model assumes that stringent idealized conditions hold. This includes market equilibrium in the housing market with perfect competition, perfect information for buyers and sellers, and a continuum of products (Singh.et al 2018). However, Benkard and Bajari (2005) state that the hedonic price model is still valid without all these conditions, noting that not all product attributes are observable. For instance, features of the surrounding environment, such as the crime level in the neighbourhood, could also have impacts on house prices.

The most common method for estimating the function shown in equation (1) is to apply a linear regression model, which is the ordinary least squares (OLS) method. However, Palmquist (1984) finds that the relationship between interior space and sale price may not be linear. Building upon that, Bin and Polasky (2004) find that a log transformation of distance variables will generally perform better than a simple linear functional form because logged variables are better able to capture the declining marginal effect of these distance variables. In addition, the log transformation is a way to reduce heterogeneity among explanatory variables because it reduces variation in the observations. After trying different functional forms (log-log, lin-log, lin-lin, log-lin), log-transformations of the dependent variable and all explanatory variables that are distance or area based are applied. The logged function of the hedonic price model is as follows:

$$ln(P_i) = \beta_0 + \sum_k \beta_k x_{ik} + \varepsilon_i \qquad (2)$$

where ln(Pi) is the natural log of the sale price of a house i; ; x_{ik} are variables of (some of which are logged) structural, neighbourhood, and the natural logs of the k location and environmental characteristics (x include *S*, *N*, *L*, *E*).

3.2 Spatial Hedonic Price Model

The modelling strategy represented by equation (2) does not account for spatial dependence where the values observed at one location depend on values at nearby locations (Lesage and Pace, 2009). It is commonly observed that housing values are influenced by prices of surrounding properties, which implies potential spatial interactions. Ignoring spatial dependence would lead to biased and inconsistent estimators (Lesage and Pace, 2009; Anselin and Arribas-Bel 2013). Detecting spatial dependence (or spatial autocorrelation) is a fundamental process of all spatial attributes. Moran's I, Geary's C, and General G are common measures for assessing whether a variable exhibits spatial dependence at a given level. In this paper, we adopt the most commonly used Moran's I to measure spatial autocorrelation.

Analysts have developed several spatial models that we briefly review. To select among available models, we conduct a log-likelihood ratio test (LR test) to see which model performs better. This is also called a common factor restriction test. If the LR test is rejected, then the added variables have significant explanatory power for the regression and should be included (Elhorst, 2014). The test results indicate that the spatial autocorrelation model (SAC) cannot be simplified into the spatial lag model and that the spatial Durbin model (SDM) cannot be simplified into the spatial error model.

The scalar parameters given in equation (3) , ρ and λ, are used to measure the magnitude of spatial dependence between units, while β and θ are K*1 vectors of response parameters that need to be estimated (Vega and Elhorst, 2013). Selecting the model that best matches the true data generating process is important for spatial analysis. For instance, if the true data generating process is a SAC model, which includes both spatial lag and spatial error, the SAR and SDM will produce unbiased coefficient estimates while SEM will produce biased estimates (Lesage and Pace, 2009). However, the SAR model ignores spatial dependence in the error terms while the SEM ignores spatial dependence in the dependent variable (Lesage and Pace, 2009). Here we report SAC as our preferred spatial model. The SAC is defined by (Anselin, 1988):

$$\begin{gathered} y = \rho W_y + \mathrm{X}\beta + u \\ u = \lambda M_\varepsilon + \epsilon \end{gathered} \tag{3}$$

where y is an $n \times 1$ vector which consists of one observation on the dependent variable for each spatial unit; W and M are $n \times n$ spatial weights matrices; X is an $n \times p$ matrix of independent variables; ρ and λ are spatial autoregressive parameters, which could measure the degree of spatial dependence in the dependent variable y and the disturbance term u respectively; β is an $p \times 1$ vector of parameters; ϵ is an $n \times 1$ vector of error terms.

Table 2 shows the decomposed effect of each spatial model. As noticed, SAR and SAC share the same direct and indirect properties. The diagonal elements are the direct effects which are the effects of the change in a particular explanatory variable in a particular unit on the dependent variable of the same unit.

The off-diagonal elements contain the indirect effects, also called spillover effects, that are the effects on the dependent variable in a location by a change in the explanatory variable of another location. One limitation of this model is that the ratio between direct and indirect effects is the same for every explanatory variable, which is unlikely to hold in practice. An alternative is to estimate the spatial Durbin model (SDM) which allows for flexible ratio between variables. We note that we also estimated the spatial Durbin model which includes spatial lags on dependent and explanatory variables. However, the SAC is still our preferred model since SDM generates many counter-intuitive results (see Appendix 1 for SDM decomposed effects).

Table 2. Direct and Indirect Effect under Different Spatial Models by Vega and Elhorst (2013)

	Direct Effect	Spillover Effect
OLS / SEM	β_k	0
SAR / SAC	Diagonal elements of $(I-\rho W)^{-1}\beta_k$	Off-diagonal elements of $(I-\rho W)^{-1}\beta_k$
SLX / SDEM	β_k	θ_k
SDM / GNS	Diagonal elements of $(I-\rho W)^{-1}[\beta_k+W\theta_k]$	Off-diagonal elements of $(I-\rho W)^{-1}[\beta_k+W\theta_k]$

The weights matrix is at the core of spatial econometric models. In this study, we implemented an inverse-distance weights matrix, which is the most frequently used weights matrix. The weights are inversely related to the physical distance between observations (houses sold in our case) and are shown in equation (4):

$$w_{ij} = \begin{cases} 1, & 0 \le d_{ij} \le d \\ 0, & d_{ij} > d \end{cases} \tag{4}$$

where d is the truncated distance (as known as bandwidth). If the distance between observation i and j is no more than d, then there is spatial correlation. The weight matrixes with threshold values ranging from 100 meters to 1000 meters were tested and the final banwidth set at 700 meters[7]. W is usually normalized to avoid singularity of the term $(I - \rho W)$ where ρ is a spatial parameter to weight the corresponding spatial lag (Seya et al., 2013; Montero et al., 2017). This paper follows the most widely used normalization, row-normalization, so that the elements of the rows sum to unity.

Estimation of most spatial econometric models is carried out using the maximum likelihood (ML) approach such that the probability of the joint likelihood for all parameters is maximized (Fischer and Wang, 2011). This approach is desirable for its consistency and asymptotic normality (Fischer and Wang, 2011; Lesage and Pace, 2009).

4. Results

4.1 Pre-estimation

One of the main concerns regarding the use of hedonic price modelling is multocollinearity. In this study, variance inflation factors (VIF) are estimated to check the extent of multicollinearity among independent variables in the SAC model. A VIF value greater than 10 implies a serious multicollinearity issue which could potentially inflate standard errors and bias estimates (Mansfield and Helms, 1982). In our analysis, all VIF values were in the range of 1.01-6.79, which are below the threshold value of 10, indicating no serious multicollinearity that would affect our model results. As indicated above, a Moran I's test was performed in the STATA software to determine the existence of spatial autocorrelation in the OLS model. According to the results (chi-sqaure=1793.15, p<0.000), the null hypothesis of no spatial correlation under selected spatial weights matrix (W=700m) is rejected. Therefore, a spatial hedonic model was used.

Appendix 2 shows the coefficients of all spatial models and OLS. Since the significance of each estimated coefficient is different between the non-spatial model and spatial models, the result from OLS model in Appendix 2 cannot be used to compare with the SAC results. Based on LeSage and Pace (2009)'s suggestion, the numerical values obtained from spatial regression are not estimates of marginal effect; therefore, direct effect and indirect effect are decomposed to illustrate true spillovers. The results are shown in Table 3. In the following discussion, the direct effect indicates the average change for all observations for the dependent variable of one house due to one-unit increase in the corresponding explanatory variable for that house. The indirect effect reflects the average spillover effects of a change in an explanatory variable of all neighbouring houses on the dependent variable of that particular house. Following the LeSage and Pace (2009)'s guideline, the effects can be recalculated into marginal dollar values[8] with one unit increase in any explanatory variables (Table 4).

Table 3. Decomposed Effects from Spatial Autocorrelation Model

Variables	Direct Effect	Indirect Effect	Total Effect
	Coefficient (Std.)	Coefficient (Std.)	Coefficient (Std.)
Living area	.000262*** (3.78e-06)	.000079*** (8.58e-06)	.00034*** (9.43e-06)
Lot size	7.41e-06*** (3.3e-07)	2.22e-06*** (2.63e-07)	9.63e-06*** (4.94e-07)
Age	-.00213*** (.000095)	-.00064*** (.000075)	-.00278*** (.00014)
Bath	.0317*** (.003)	.00951*** (.00135)	.0412*** (.00399)
Bed	-.0132*** (.00247)	-.00395*** (.00083)	-.0171*** (.00321)
Condition	.0494*** (.00281)	.0148*** (.00187)	.0643*** (.00607)
Basement	.0846*** (.00306)	.0254*** (.00297)	.11*** (.00496)
Parking	.0601*** (.00264)	.018*** (.00212)	.0781*** (.0039)
Season	.0168*** (.00264)	.00504** (.00097)	.0218*** (.0035)
Downtown	-.0398*** (.0114)	-.0119*** (.0237)	-.0517*** (.015)
LRT	.00638 (.00581)	.00191 (.00174)	.0083 (.00754)
Density	-6.16e-06** (2.45e-06)	-1.85e-06** (7.63e-07)	-8e-06** (3.19e-06)
Child	.000613 (.000923)	.000184 (.000277)	.0008 (.001199)

Elder	.00125***	.000375***	.00163***
	(.00037)	(.000117)	(.00048)
Unemployment	-.0071	-.000213	-.00093
	(.00168)	(.00051)	(.00219)
Low Income	.000045	.0000136	.000059
	(.00041)	(.000123)	(.00063)
High Income	.00163***	.000489***	.00212***
	(.0004)	(.000118)	(.00051)
Bachelor	.00202***	.000607***	.00263***
	(.000363)	(.00011)	(.000456)
Crime Incidence	-.00059***	-.000178***	-.00077***
	(.00021)	(.00006)	(.00027)
Quality	.00235	.00071	.00306
	(.00164)	(.00049)	(.00213)
Agricultural	.0152***	.00455***	.0197****
	(.00383)	(.00128)	(.00503)
Woodland	-.0232***	-.00696***	-.0302***
	(.00227)	(.00096)	(.00296)
Non-developable	-.0064***	-.00193***	-.00838***
	(.00175)	(.00057)	(.00229)
UA Farm	-.088***	-.0264***	-.1143***
	(.0101)	(.00364)	(.01302)
Land-use Change	.000012	3.7e-06	.000016
	(.000016)	(4.81e-06)	(.000021)

Notes: ***, **, * indicate significance at 1%, 5%, and 10% level respectively.

Table 4. Marginal Willingness to Pay for Direct and Indirect Effect on all Variables

Variables	Willingness to Pay (WTP)	
	Direct Effect	Indirect Effect
Living area	$118	$36
Lot size	$3	$1
Age	$954	$291
Bath	$168,71	$4325
Bed	-$6,003	-1,796
Condition	$22,464	$6,730
Basement	$38,471	$11,550
Parking	$27,330	$8,185
Season	$7,640	$2,292
Downtown	-$2,363	-$706
LRT	_	_
Density	-$3	-$1
Child	_	_
Elder	$568	$171
Unemployment	_	_
Low Income	_	_
High Income	$741	$222
Bachelor	$919	$276
Crime Incidence	$286	-$81
Quality	_	_
Agricultural	$2721	$815
Woodland	-$31,969	-$9,591
Non-developable	-$17,119	-$5,163
UA Farm	-$5,046	-$1,514
Land-use Change	_	_

4.2 Empirical Results

Results on Table 3 show that the direct and indirect effects of all structural variables are statistically significant. Home buyers have higher willingness to pay for (a) larger living area, (b) larger lot size, (c) more bathrooms, and (d) more parking spaces. Specifically, increasing one square foot of living space would generate 0.026% ($118) higher property value for the house and increase neighbour's house prices by 0.0079%. The number of parking spaces is statistically and economically significant: increasing one more parking space could raise the house's property value by 6.01% ($27,330) and increase the value of neighbours' houses by 1.8% ($8,185). Compared with the number of bathrooms, increasing the number of bedrooms significantly decreases property value. The reason may be that a house with more bedrooms, but equal in size to a similar house, would have smaller bedrooms, or possibly more bedrooms in the basement that would reduce space available for recreation. A house with more bedrooms may also house more people, with more wear and tear on the house. The results also indicate that people have higher willingness to pay for a finished basement, which could increase their property value by 8.46% ($38,471). People also prefer a house in better condition. Age is found to have significant negative direct and spillover effects. If the house is built one year earlier, that would decrease the property value by 0.21% ($954) and also decrease surrounding properties' values by 0.064% ($291). The seasonal effect of houses sold matches our hypothesis. Both direct and indirect seasonal effects show that houses sold between April and September have higher prices.

Distance to downtown has significant impact on house price. If the house is 1km further away from the downtown area, its property value will decrease by $2,363. Meanwhile, the value of the neighbour's houses will decrease by $706. Despite the negative externalities such as traffic noise and congestion, people are still willing to pay more for houses located nearer to the city centre. Surprisingly, proximity to the nearest LRT station is shown to have no significant impact on house value. This might imply that convenience trades off with the negative effects of the nuisance and congestion effects of the LRT stations.

The results for some of the neighbourhood variables are consistent with our prior hypotheses, others inconsistent. As expected, we found population density to have negative direct and indirect effects, indicating that people prefer to live in less densely populated neighbourhoods. Crime incidence within the neighbourhood has a negative effect, with each additional crime per year decreasing house price by 0.059% ($286). Proportions of older, high-income and university-educated people have positive direct and indirect effects, while the proportion of children has no significant effect. We were surprised that unemployment rate, proportion of low-income people, and elementary school quality had no affect on house prices.

It is noteworthy that all open space attributes were found to have significant impacts on house prices, most were positive and one was negative. People are willing to pay more to live closer to woodlands, non-developable open space (parks) and the University of Alberta South Campus farm, but willing to pay less to live closer to agricultural open space. To capture effects of different types of open space, we conduct t-tests showing that these four open space types are significantly different from each other (Table 5). The direct and spillover effects of distance to (large-scale) agricultural land are both positive and significant. With 1km further from agricultural land, the property value increases by $2,721 and neighbourhood's property value increases by $815. People may be less likely to consider living near farmland due to the odor, dirt, noise and other negative externalities associated with agricultural production. Although the University of Alberta farm is one type of agricultural open space that can also generate some of the same negative effects for nearby residents, it appears that people place different value on it as indicated by the negative sign on its direct and indirect coefficients. With 1km closer to University of Alberta farm, property value increases by $5,046. People would pay more to live near this farm, possibly due to the scenic views and recreation services it provides, and the sense of permanence of the university ownership. The same result arises with proximity to woodlands, which includes shrubland and forest land. Locating 1km closer to woodlands and non-developable lands would bring $31,969 and $17,119 increases in house price respectively. Closer proximity to forests, shrub land, and non-developable parks and water bodies increases own house prices and prices of neighbouring houses. This is consistent with the findings of McConnell and

Walls (2005) and Luttik (2000). That implies that people make their residential location based on the scenic view and recreational uses of these non-developable lands, and the same impact is shown in their neighbours' house prices. The result shown for the land-use change variable is negative, but not significant, indicating that recent nearby development has no significant impact on people's house purchase decisions.

Table 5. T-test of Open Space Variables

Variables	Mean	Std. Err.	$Pr\ (\lvert T \rvert > \lvert t \rvert)$
Developable Agricultural Land	0.184	0.011	0.0000
U of A farm	1.886	0.007	
Developable Agricultural Land	0.184	0.011	0.0000
Woodland	-1.441	0.009	
Developable Agricultural Land	0.184	0.011	0.0000
Non-developable land	-2.096	0.009	
Woodland	-1.441	0.009	0.0000
Non-developable land	-2.096	0.009	
Woodland	-1.441	0.009	0.0000
U of A farm	1.886	0.007	
Woodland	-1.441	0.009	0.0000
U of A farm	1.886	0.007	

5. Limitations and Implications

In this study, a hedonic pricing model is coupled with a spatial econometric approach in order to investigate: (a) the marginal effects of open space on property value, as well as (b) the spatial spillovers in these effects. The results obtained from a spatial Autocorrelation model under a ML estimation confirms the existence of spatial correlation on open spaces and other contextual variables, suggesting that the use of Ordinery Least Square (OLS) hedonic model would be inappropriate and less precise for this analysis.

In interpreting the results, some limitations of spatial models should be kept in mind. One limitation of spatial models is the spatial weights matrix, which needs to be specified in advance and cannot be estimated (Leeders, 2002). Several approaches to improve the specification of the spatial weights matrix are summarized in Elhorst (2010). Although a common practice is to test the robustness of the specification of the spatial weights matrix, different constructions (e.g. k-nearest, distance-based, rock/queen/king contiguity, etc.) would complicate the selection of model and interpretation of results. Another complicating factor that often arises in open space studies is the representation of open space. Studies have shown that other factors such as size of open spaces, soil quality, water quality, orientation of the houses, and accessibility of open spaces can also affect property values. This study uses proximity to the nearest open spaces as the only measure of open space benefits or costs. We encourage future studies to include more attributes of open space to increase the robustness of the results. In addition, the data we used for agricultural open space, woodland and the wetland in non-developable open space retrieved from AAFC website largely ignores open spaces that are less than 900 square meters (Landsat pixels are 30m x 30m pixels), such as many community gardens and playgrounds. Our results are thus relevant for larger scale commercial agriculture.

It is worth noting that, although not included in the objectives of this paper, the hedonic price analysis has quantified the marginal effects of a large set of significant variables, thus providing additional information of policy relevance. The results from the Spatial Autocorrelation model show 19 of 25 variables to be significant (Table 3), mostly structural and neighbourhood variables, with most results consistent with our hypotheses. This information may be useful for developers and urban planners considering neighbourhood structure and housing design.

Among the open space variables, we are particularly interested in the effect of farmland on nearby house price. Given people's preference to live further from large-scale farmland, there is pressure for continual fragmentation and loss of farmland at the periphery of the city. This is consistent with the insight provided by Bergstrom and Ready (2008) that people living on the city edge are likely to favor land development to produce relatively scarce urban benefits, while people living in the core of the city will favour more dense urban development since they perceive peri-urban land conversion as a loss of open space value, without meaningful change in urban amenity or farmland disamenity value. This study further confirms this statement since property value is lower near farmland. Therefore, under this circumstance, people might exhibit NIMBYism (not in my backyard) even though they still want to conserve farmland within the city-region landscape. Scholars have used the term NIMBY to describe residents who disagree with locating a significant public service facility that may bring negative externalities near their houses, although they recognize the importance of that facility to the overall area (Whittemore and BenDor, 2018). Agricultural land might have been treated as an object of NIMBYism because of the odor, noise and other negative impacts associated with commercial-scale farming. This leads to a clear outcome for farmland conservation. When the government designs the land re-zoning on a parcel-by-parcel basis, it is likely to consider taxpayers' willingness to pay and acceptance by local residents. In this situation, it might be difficult to achieve farmland conservation within the city. Eventually, the agricultural land around the edges of the city will all be converted to residential or industrial land, contributing to unending urban sprawl unless checked.

Balancing the private and public values of the different types of open space requires governments to take a longer-term approach to the designation and protection of all types of open space, including agricultural open space. Conservation easements could provide greater certainty about future development, while shared bicycle / walking path could enhance the public values of those lands. Another suggestion is to implement Transferable Development Credits (TDC) in which landowners in a designated conservation area could sell development credits to developers who want to develop and build in a designated development area.

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Appendix

Appendix A. Decomposed Direct and Indirect Effects under Spatial Durbin Model

Variables	Direct Effect	Indirect Effect	Total Effect
Living area	.0002646***	.0002359***	.0005005***
	(3.78e-06)	(.0000344)	(.0000349)
Lot size	8.05e-06***	.0000473***	.0000553***
	(3.44e-07)	(6.25e-06)	(6.36e-06)
Age	-.0022422***	-.0003137	-.0025559***
	(.0000954)	(.000762)	(.0007767)
Bath	.0317019***	-.0630623**	-.0313604
	(.0030242)	(.0275825)	(.0283556)
Bed	-.0185662***	-.1629592***	-.1815254***
	(.0025372)	(.0261139)	(.02689)
Condition	.0495443***	.0666251**	.1161694***
	(.0028867)	(.02707)	(.0280076)
Basement	.0849252***	.1402238***	.225149***
	(.0031222)	(.0289208)	(.0298682)
Parking	.0600378***	.0552259**	.1152636***
	(.0026752)	(.025149)	(.0258446)
Season	.0166299***	-.0054796	.0111503
	(.0027857)	(.027678)	(.028785)
Downtown	.0317036*	-.2192675***	-.1575639***
	(.0366352)	(.0496338)	(.0229153)
LRT	.0183757	-.0245515	-.0061758

	(.0149765)	(.0199134)	(.0098157)
Density	3.07e-06	-9.03e-06	-5.96e-06
	(3.66e-06)	(9.56e-06)	(7.52e-06)
Child	.005099***	.0048221	.0039987
	(.001903)	(.0033042)	(.0026066)
Elder	.0010732**	-.002236	-.0011629
	(.000531)	(.001457)	(.0012181)
Unemployment	.0039126*	-.0190585***	-.0151458***
	(.0022885)	(.006841)	(.0057087)
Low Income	.0008723*	-.0046562**	-.0037839**
	(.000523)	(.0018364)	(.0015789)
High Income	.0034389***	-.0077379***	-.004299***
	(.0005257)	(.0014925)	(.0012427)
Bachelor	.0036453***	-.0035978***	.0000475
	(.0005055)	(.0011941)	(.0009565)
Crime Incidence	-.00001898	-.001544**	-.0017338***
	(.00002757)	(.000769)	(.0006373)
Quality	-.0012353	.0172485***	.0160133***
	(.0022861)	(.0062183)	(.0050039)
Regional factor	.029318	-.0194748	.0098431
	(.009826)	(.0255546)	(.0203345)
Agricultural	.0077031	-.0085633	-.0008602
	(.007346)	(.0140554)	(.0105578)
Woodland	-.0260541***	.308287***	.0047746
	(.0026306)	(.0119429)	(.0108785)

Non-developable	-.0049834***	-.0291004**	-.0340838***
	(.001867)	(.0130083)	(.0124561)
UA Farm	.0471643*	-.0792119**	-.1263762***
	(.0286235)	(.0366096)	(.0190186)
Land-use Change	.0000247	.0002852***	.0003099***
	(.0000166)	(.0000695)	(.0000695)

Appendix B. Results from all spatial models

Variables	OLS	SAR	SEM	SAC	SLX	SDM	SDEM	GNS
Living area	.00028***	.00025***	.000266***	.00026***	.000027***	.00026***	.000262***	.00026***
	(3.87e-06)	(3.81e-06)	(3.79e-06)	(3.79e-06)	(4.04e-06)	(3.81e-06)	(3.8e-06)	(3.8e-06)
Lot size	8.32e-06***	7.75e-06***	7.41e-06***	7.4e-06***	7.1e-06***	7.07e-06	7.2e-06***	7.1e-06***
	(3.55e-07)	(3.36e-07)	(3.29e-07)	(3.29e-07)	(3.49e-07)	(3.28e-07)	(3.29e-07)	(3.3e-07)
Age	-.00205***	-.0019***	-.00215***	-.0021***	-.00226***	-.00224***	-.00222***	-.0022***
	(.000098)	(.00009)	(.0000954)	(.000095)	(.000101)	(.000095)	(.000095)	(.000095)
Bath	.0266***	.00254***	.0332***	.0316***	.032***	.033***	.032***	.0322***
	(.00321)	(.00304)	(.00298)	(.00299)	(.00314)	(.00296)	(.00302)	(.00297)
Bed	-.0215***	-.0136***	-.0148***	-.0131***	-.0183***	-.0152***	-.0164***	-.0157***
	(.00267)	(.00254)	(.00245)	(.00246)	(.0026)	(.00245)	(.00251)	(.00247)
Condition	.0525***	.0516***	.048***	.0492***	.0489***	.0482***	.049***	.0486***
	(.00305)	(.00289)	(.00279)	(.0028)	(.00296)	(.00278)	(.0029)	(.0028)
Basement	.0935***	.0889***	.0828***	.0843***	.0846***	.082***	.0842***	.0827***
	(.0033)	(.00312)	(.00303)	(.00304)	(.00321)	(.00303)	(.0031)	(.00305)
Parking	.0661***	.0592***	.0603***	.0598***	.0603***	.0589***	.0603***	.059***
	(.00284)	(.0027)	(.00263)	(.00263)	(.0028)	(.00262)	(.0027)	(.0026)
Season	.01581***	.0159***	.0166***	.0167***	.0164***	.0167***	.0168***	.0167***
	(.00292)	(.00276)	(.0026)	(.00263)	(.0028)	(.00264)	(.0027)	(.00266)
Downtown	-.0592***	-.0454***	-.0218	-.0396***	.1489***	.0663*	.0857*	.079*
	(.00632)	(.006)	(.0147)	(.0113)	(.0398)	(.0376)	(.049)	(.0414)
LRT	.00679**	.00102	.0122	.00635	.0382**	.019	.0175	.0194
	(.00303)	(.00287)	(.0076)	(.00579)	(.0163)	(.0153)	(.0195)	(.0167)
Density	-.00001***	-8.43e-06***	-5.47e-06**	-6.1e-06**	8.53e-06**	3.3e-06	3.46e-06	3.59e-06
	(1.7e-06)	(1.62e-06)	(2.75e-06)	(2.44e-06)	(4.03e-06)	(3.8e-06)	(4.55e-06)	(4.05e-06)
Child	.00082	.00061	.00069	.00061	-.0007	-.00092	-.00168	-.0011
	(.00064)	(.000604)	(.00103)	(.00092)	(.00146)	(.00138)	(.0016)	(.00146)
Elder	.00089***	.00096***	.00132***	.00013***	.00158***	.0011**	.00088	.00107*
	(.00026)	(.00025)	(.000413)	(.000365)	(.00058)	(.00054)	(.00064)	(.00058)
Unemployment	-.0031**	-.0036***	.00175	-.00071	.00905***	.0043*	.00354	.0043*
	(.00123)	(.0012)	(.00184)	(.00167)	(.00252)	(.0024)	(.00278)	(.0025)
Low Income	-.00054*	-.00062**	.000304	.000045	.00118**	.00097*	.00098	.00099*
	(.00032)	(.000304)	(.00044)	(.00041)	(.00058)	(.00055)	(.00063)	(.00057)

High Income	.00167***	-.00019	.00279***	.00163***	.00466***	.0036***	.0028***	.00347***
	(.000278)	(.00027)	(.000425)	(.0004)	(.00058)	(.00055)	(.00064)	(.00058)
Bachelor	.0024***	.00059**	.0033**	.00202***	.00441***	.00372***	.0035***	.00367***
	(.00024)	(.00023)	(.00039)	(.000167)	(.00055)	(.000522)	(.00061)	(.00055)
Crime Incidence	-.00147***	-.00055***	-.00071***	-.00059***	.00014	-.00016	-.00021	-.00016
	(.00015)	(.00014)	(.00023)	(.000204)	(.000303)	(.00029)	(.00033)	(.0003)
Quality	.00838***	.00354***	.0027	.00234	-.00467*	-.0016	-.0036	-.0024
	(.00117)	(.0011)	(.00182)	(.00163)	(.00252)	(.00237)	(.0027)	(.0025)
Agricultural	.0151***	.0167***	.0126***	.0151***	.0018	.00788	.0113	.0087
	(.00258)	(.00245)	(.00437)	(.00382)	(.0067)	(.0063)	(.0076)	(.00674)
Woodlands	-.0246***	-.0193***	-.0264***	-.0231***	-.0265***	-.0267***	-.0269***	-.0268***
	(.00194)	(.00185)	(.00236)	(.002267)	(.00293)	(.00276)	(.00304)	(.0029)
Non-developable	-.00859***	-.0078***	-.00643***	-.0064***	-.00265	-.00438**	-.0045**	-.0043**
	(.00167)	(.00158)	(.00179)	(.0017)	(.0021)	(.00198)	(.0021)	(.00202)
UA farm	-.11***	-.0808***	-.1115***	-.0876***	-.0661**	-.0455	-.0028	-.0361
	(.00541)	(.0052)	(.01313)	(.0101)	(.0311)	(.0293)	(.034)	(.0314)
Land-use change	.000059***	.000034**	.000014	.000012	.000026	.000019	.000027*	.000023
	(.000014)	(.000014)	(.000016)	(.000016)	(.000018)	(.000017)	(.0000163)	(.000017)
Regional factor	.0237***	-.00052	.0308**	.0163**	.0328***	.0297***	.0303**	.03***
	(.0049)	(.0047)	(.0078)	(.00709)	(.0108)	(.01012)	(.0117)	(.0107)
Constant	12.49***	7.13***	12.35***	9.41***	12.68***	4.62***	12.44***	6.49***
	(.0252)	(.174)	(.0435)	(.253)	(.0471)	(.253)	(.085)	(.798)
W*Living area					.000115***	-.00008***	.00012***	-.000031
					(.000014)	(.000014)	(.000017)	(.000024)
W*Lot size					.000032***	.000013***	.000023***	.000017***
					(2.43e-06)	(2.36e-06)	(3.21e-06)	(2.92e-06)
W*Age					-.00057*	.0013***	.00018	.001***
					(.00031)	(.0003)	(.00039)	(.00035)
W*Bath					-.0569***	-.044***	-.014	-.0381***
					(.0111)	(.0104)	(.0127)	(.0115)
W*Bed					-.0849***	-.051***	-.056***	-.054***
					(.01001)	(.0095)	(.011)	(.0101)
W*Condition					.0372***	-.0058	.0253**	.0035
					(.0107)	(.01012)	(.0118)	(.0113)
W*Basement					.0832***	-.00011	.0574***	.0177

	(.0113)	(.011)	(.0126)	(.0133)
W*Parking	.0201**	-.0168*	.041***	-.0029
	(.01)	(.0095)	(.0112)	(.0119)
W*Season	-.0051	-.0127	.0015	-.0089
	(.0108)	(.0102)	(.0111)	(.0107)
W*Downtown	-.2779***	-.124***	-.195***	-.152***
	(.0439)	(.0416)	(.058)	(.0471)
W*LRT	-.04**	-.0211	-.0184	-.0217
	(.0177)	(.0167)	(.0236)	(.0184)
W*Density	-.000018***	-5.43e-06	-.000012	-7.4e-06
	(5.89e-06)	(5.56e-06)	(8.63e-06)	(6.3e-06)
W*Child	.00279	.0024	.0043	.0027
	(.0021)	(.0019)	(.0031)	(.0022)
W*Elder	-.00244***	-.0015*	-.00092	-.0015*
	(.00086)	(.00081)	(.00125)	(.00091)
W*Unemploymen	-.0232***	-.0098***	-.011*	-.0109**
	(.00395)	(.0037)	(.00596)	(.00423)
W*Low Income	-.00343***	-.0023**	-.0031**	-.00263**
	(.001)	(.00095)	(.00153)	(.00108)
W*High Income	-.00689***	-.0052***	-.00258*	-.0049***
	(.00087)	(.00082)	(.00133)	(.00094)
W*Bachelor	-.00307***	-.0037***	-.00258**	-.0035***
	(.00075)	(.00071)	(.0011)	(.0008)
W*Crime Inciden	-.000205***	-.00047	-.001	-.0067
	(.00045)	(.00043)	(.00068)	(.00049)
W*Quality	.0191***	.0074**	.0183***	.0107**
	(.00375)	(.0035)	(.0055)	(.0042)
W*Agricultural	.00695	-.0082	-.0066	-.0074
	(.00915)	(.0086)	(.0133)	(.00965)
W*Woodland	.0174***	.0284***	.0203**	.0264***
	(.00595)	(.0056)	(.009)	(.0065)
W*Non-	-.0261***	-.0081	-.0135	-.0108*
developable	(.0059)	(.0056)	(.0086)	(.0064)
W*UA farm	-.0385	-.00058	-.118***	-.0264

					(.033)	(.0311)	(.0403)	(.0352)
W*Land-use					.0002***	.00009***	.000129***	.00011***
change					(.000032)	(.00003)	(.000047)	(.000034)
W*Regional Facto					-.0173	-.0261*	-.0198	-.0243
					(.0157)	(.0148)	(.0226)	(.0165)
ρ		.419***		.2336***		.635***		.485***
		(.0135)		(.0199)		(.0197)		(.0642)
λ			.745***	.608***			.668***	.232***
			(.0171)	(.235)			(.0203)	(.0791)
Wald test		970.47***	1903.36***	1456.4***	817.93***	1961.98***	1713.4***	1551.37***
R-squared	.8258	.8191	.8216	.8227	.8396	.8384	.836	.8385
Number of Observations	9495							

[1] In Edmonton, there are 400 neighbourhoods in total with an average size of 1.96 square kilometer.

[2] Edmonton's elementary schools have defined catchment areas, mostly related to specific neighbourhoods. In order to examine the quality of schools, 2017 school quality score calculated by the Fraser Institute (Fraser Institute) provides us with a range from 0 to 10. The rationale behind using the 2017 score instead of the 2016 score is because neighbourhood structure plans always state the designated schools 2 years before the school is ready for use. Two of the Elementary Schools, Ivor Dent and Mayfield, do not have their scores posted on the Fraser Institute website due to low attendance and high percentage of special needs students, an average score of 5.8 is recorded for each of them.

[3] The raster data layers on actual land use are downloaded from Government of Canada Annual Crop Inventory website (Government of Canada).

[4] Developable agricultural land is land that is suited for producing agricultural products, which includes cropland, pastureland and grassland.

[5] Woodland includes forest land and shrubland which is also an actual land use rather than permitted land use.

[6] Non-developable land includes water bodies, parks and wetlands while water bodies and parks are obtained from Open Data Edmonton Portal.

[7] Among test results, 700m shows the highest significance level. Also, it is consistent with our neighbourhood size, which is provided by the Open Edmonton Dataset. In Edmonton, the median size of residential neighbourhoods is 1.18km^2, thus the radius of 700m from any particular house will cover most of the relevant neighbourhood. Shorter threshold distances also have the advantage of having land-related variables that are more intuitive to interpret.

[8] MWTP for non-logged variable $y * \beta$. MWTP for logged distance variable is $\beta * \frac{y}{x}$. y denotes the mean value of house price ($454,736) and x is the mean value of explanatory variable shown in Table 1.