Does Municipal Development Policy Affect Property Values: A Quasi-Experimental Hedonic Model Approach in Alberta, Canada

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Abstract:

Rapid economic and demographic growth is changing the nature of Alberta's urban and rural landscapes. This has had profound effects on land use, particularly in areas near to Edmonton and Calgary where there is great concern about urban sprawl into surrounding farmlands. In 2012, town of Okotoks shifted from a finite growth policy to a continuous growth policy, thus eliminating a key policy constraint on urban development. This policy history makes Okotoks a "natural experiment" of land use policy. We selected Okotoks to reveal people's willingness to pay for open spaces, and most importantly, the causal effects of the municipal development policy on property values. Our study is based on a hedonic price approach with a spatial lag model as well as a spatial two-stage least squares. Under residential property transactions from 2010 to 2017 in Okotoks and surrounding area, we chose properties with developable lands in a 200-meter buffer as a treatment group, and those without developable lands as a control group, to incorporate Difference-in-Difference into the estimations. Results showed that people value pastures and forests within the 200-meter buffer, but disvalue the municipal policy of continuous growth. Individuals are willing to pay to avoid that policy.

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Keywords: difference-in-difference, hedonic price model, open space, policy change

INTRODUCTION

Parks, forests, greenbelts and agricultural lands are open spaces that provide recreational services, aesthetic experiences, agricultural products, climate regulation, watershed protection, and wildlife habitat. The Canadian province of Alberta has diverse landscapes, including glaciers, mountains, foothills, lakes, rivers, forests and open plains[1]. There are large expanses of grasslands and parklands in the south and southwest areas of the province, although 75% of the grasslands have been put into crop production. Meanwhile, Alberta has a large and vibrant agricultural industry. In 2016 the province had 40,638 farms second only to Ontario among Canadian provinces (Statistics Canada 2016a).

However, a trend of rapid urban growth has resulted in the conversion of large areas of agricultural lands to non-agricultural uses, such as industrial, commercial and residential lands (Alberta Agriculture and Forestry 2016). Urban residents move to lower cost housing areas at the urban fringes, thus stimulating suburban development on undeveloped lands. Alberta's two largest cities, Calgary and Edmonton, had the fastest growing populations in Canada between 2006 and 2011 and between 2011 and 2016 (Statistics Canada 2016b). It is acknowledged that urban sprawl does not happen automatically, but is driven by government planning policies. Since urbanization threatens open spaces, people want to assess the values of those lands, evaluate land-use policies, and propose options for open space conservation (Geoghegan et al. 2003, Kovacs and Larson 2007). Two Alberta laws, governing land use and municipal governance, mandate municipal governments to take steps to conserve prime farmland.

Open spaces have characteristics of non-market goods and thus revealed preferences and stated preferences are the main approaches available to estimate their values (Bockstael and McConnell 2007). Revealed preference studies using models such as travel cost and hedonic price are based on individuals' actual behaviors and thus satisfy internal validity requirements (Bockstael and McConnell 2007).

Based on the property value dataset we had, our study follows a hedonic price model, assuming that the values that individuals place on open spaces are capitalized into housing prices. Previous studies have considered the value of forests (Cho et al. 2008), parks (Hoshino and Kuriyama 2009), and agricultural lands (Geoghegan et al. 2003) on housing prices. Geoghegan et al. (2003) found that home buyers place higher value on permanent than

[1] Source: http://www.albertacanada.com/business/overview/location-and-geography.aspx.

developable areas of open space.

Because individuals value open spaces, they will consider land uses and designation policies while buying a house. In other words, land-use regulations may also have influences on housing prices. Using Difference-in-Difference (DID) method to incorporate the regulation into a hedonic price framework, we estimated people's WTP for such a policy. A few previous studies have attempted to do this. For example, Heintzelman (2010) found that the Community Protection Act in the U.S. state of Massachusetts had no significant impacts on property values in the short run. No Kim et al. (2016) found that the water management agreement for the Chestermere Lake in Alberta resulted in an increase in house prices. While current studies focused on preservation policies, our study analyzed a policy change that encouraged more rapid urban development. To our knowledge, few if any previous studies have combined DID and spatial effects in the same model. It is very common in a real estate market that nearby dwelling prices are spatially dependent, in view of the influences of common culture, policy, facilities, and recreational amenities.

Based on residential property values from 2010 to 2017 around the Town of Okotoks, Alberta, we estimated a spatial lag model, and a spatial two stages least squares (S2SLS) model with heteroscedasticity and autocorrelation consistent (HAC) standard errors. Direct impacts as well as spillover impacts were both revealed. We found that people value pastures more than forests, but disvalue the policy. The results are as expected.

STUDY AREA DESCRIPTION

In the context of Alberta, we chose the Town of Okotoks as a natural experiment for our study. Figure 1 displays the location of Okotoks. Only 18 kilometers south of the City of Calgary, Okotoks faces a number of pressures to expand its area and services.

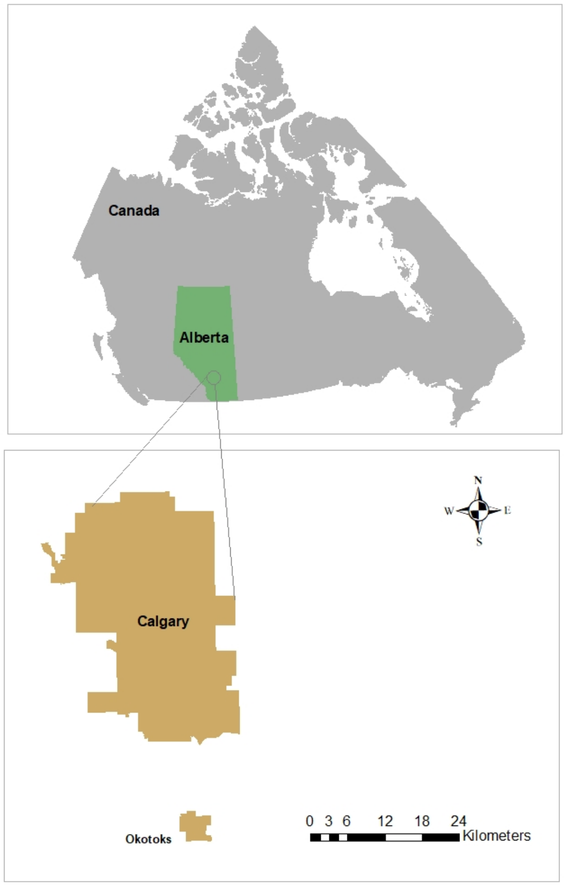

Figure 1: Reference map of the Town of Okotoks

Okotoks was constrained to a limited water supply[2]. In 1998, Okotoks issued a Municipal Development Plan (MDP), in favor of a “small town atmosphere” and a “sustainable Okotoks”. It said that the population of the town would be held to 30,000 to 35,000 residents for a 20-year horizon. Meanwhile, growth would not occur beyond existing neighbourhood areas. In order to protect natural as well as recreation areas, MDP required a healthy urban forest, 95% preserved environmentally significant lands, and 20% of gross land as public spaces and pathway systems (Town of Okotoks 1998). The Town Council referred to this as a finite growth policy. However, development pressures from the growth of the Calgary region, and the establishment of country residential subdivisions near the town’s boundaries promoted the Okotoks Council to switch from the finite growth policy to a continuous growth policy in September 2012. Such policy

[2] Source: http://www.mtroyal.ca/library/inc/cprs/pdfs/7-01-WEI-13%20Weigel,%20Nancy.pdf.

increased the target population to 60,000 for a 60-year plan. It allowed for further urban development, which suggested at least 8 housing units per gross developable acre (Town of Okotoks 2014). Total net lands required were predicted to be 543 hectares for a first 30-year plan and 399 hectares for a second 30-year plan (Town of Okotoks 2014).

Our study revealed people's WTP for the continuous growth policy. In order to capture spatial dependence among dwellings, and meanwhile keep all properties in similar real estate markets, we enlarged the study area into 4 townships with 2 km buffers surrounding Okotoks. It is shown as in Figure 2.

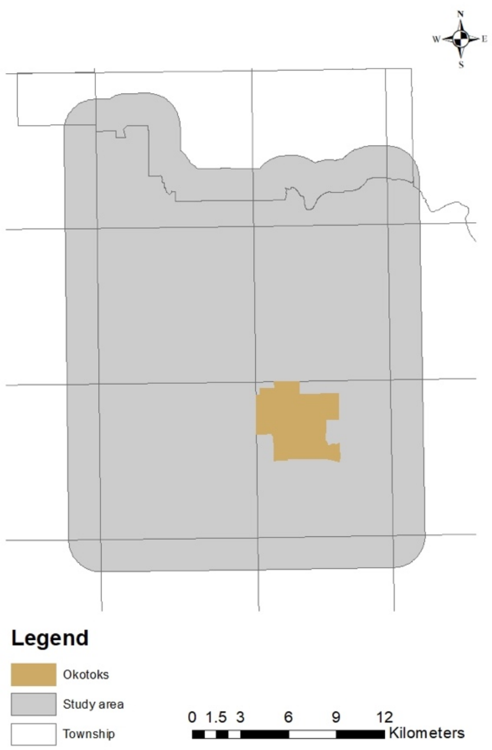

Figure 2. A map of the study area

THEORETICAL FRAMEWORK

Hedonic price method

Hedonic price method is one of the revealed preference estimations. It is assumed that goods are differentiated. The observed price of a product is a combination of implicit prices of different attributes (Rosen 1974). The hedonic price technique is popular in property markets. Along with property transaction prices, this method has been used to estimate WTPs for various characteristics, such as the effect of proximity to ethanol plants (Zhang et al. 2012), the recreational value of water (Jr and Jones 1995), and the externality effects of waste sites (Ihlanfeldt and Taylor 2004).

For residential properties, there are structural characteristics, locational characteristics, neighborhood characteristics and environmental amenities capitalized into the price (Boxall et al. 2005, Bin et al. 2009). The housing prices can thus be specified as:

$$P_{it} = \beta_0 + \boldsymbol{\beta}_1'\boldsymbol{S}_{it} + \boldsymbol{\beta}_2'\boldsymbol{L}_{it} + \boldsymbol{\beta}_3'\boldsymbol{N}_{it} + \boldsymbol{\beta}_4'\boldsymbol{E}_{it} + \varepsilon_{it} \quad (1)$$

where subscripts i and t represent property and time; P_{it} is a housing price; $\boldsymbol{S}_{it}$ is a vector of structural characteristics, including living area, numbers of bedrooms and et al.; $\boldsymbol{L}_{it}$ is a vector of locational attributes, such as the distance to employment centers; $\boldsymbol{N}_{it}$ is a vector of neighborhood characteristics, including the median household income, and levels of education; $\boldsymbol{E}_{it}$ is a vector of environmental amenities, including the amount of open spaces within a certain buffer; and ε_{it} is an error term.

Prices of properties are determined by supply and demand, so the hedonic price model is discussed at the point that sellers and buyers are in equilibrium (Bockstael and McConnell 2007). In a particular property market, a consumer's utility could be expressed as:

$$U = U(Z, S, L, N, E) \quad (2)$$

where Z is a composite good and the price is one; and S, L, N and E are attributes of the house.

The consumer has a budget constraint presented as below:

$$I = Z + P \quad (3)$$

where I is the homebuyer's income, and P is the housing price.

It is assumed that q is a specific attribute for this property through L, N or E. Maximizing utility, the individual will choose a property that satisfies equation (4) as:

$$\left(\frac{\partial U}{\partial q} / \frac{\partial U}{\partial Z}\right) = \frac{\partial P}{\partial q} \tag{4}$$

where $\frac{\partial P}{\partial q}$ is the implicit price of a property characteristic.

Such estimation reflects demand and supply interactions in the housing market, which is denoted as a "first stage" hedonic analysis (Bockstael and McConnell 2007). The "second stage" analysis, based on characteristics of households, could estimate the inverse demand function for q. Households' demand curves for attributes are different, as are the WTPs for an extra unit of an attribute. WTPs are the most accurate welfare measure (Bockstael and McConnell 2007). Because households' characteristics such as income and family size are not available, we only discuss the "first stage" estimation, and it is used as an approximate estimation of the marginal willingness to pay (MWTP) for this specific attribute.

Difference-in-Difference method

Because of the presence of measurement error, omitted explanatory variables and sample selection from a non-randomized population, estimations may be biased. In order to control for unobserved factors, we could use an experiment or quasi-experiment approach (Greenstone and Gayer 2009). However, it is difficult to perform a randomization in a real estate market. Usually researchers attempt to use different quasi-experiments to figure out a counterfactual then identify the causal impact of a change.

DID is one of quasi-experiments (Atreya et al. 2013). It includes one assignment, two groups and at least two periods. Treatment and control groups have a common trend before the assignment, which is also called the first period. Then in the second period, only participants will receive the treatment. The effect of treatment on outcomes is expressed as:

$$ATE = \{E[y_{11}] - E[y_{10}]\} - \{E[y_{01}] - E[y_{00}]\} \tag{5}$$

where ATE is the average treatment effect; $E[y_{11}] - E[y_{10}]$ is the difference of outcomes for treatment group; $E[y_{01}] - E[y_{00}]$ is the difference of outcomes for control group.

EMPIRICAL ANALYSIS

Ordinary least squares (OLS) regression assumes that all observations are not correlated with each other. The error terms are homoscedastic and independent. For example, if observations are independent, explanatory variables of region i have no influence on the dependent variables of region j. However, spatial econometrics is performed when observations are spatially dependent with each other (LeSage and Pace 2009). Spatial dependence very common in a real estate market. Nearby dwelling prices are spatially dependent. This phenomenon occurs because all regions are in a particular geographic space (LeSage and Pace 2009).

If spatial dependence is present, OLS estimates will still be unbiased but inefficient. What researchers normally perform in such instances are spatial models.

Spatial lag model

The spatial lag model (SLM) presents only the endogenous interaction effects among dependent variables. The model with interaction effects is shown in equations (6), (7) and (8).

$$Y = \rho WY + \alpha\iota + X\beta + \varepsilon \tag{6}$$

$$Y = (I_n - \rho W)^{-1}\alpha\iota + (I_n - \rho W)^{-1}X\beta + (I_n - \rho W)^{-1}\varepsilon \tag{7}$$

$$\varepsilon \sim N(0, \sigma^2 I_n) \tag{8}$$

where Y is an $(n\times1)$ vector of observations; X is an $(n\times k)$ matrix of explanatory variables; $\alpha\iota$ is an $(n\times1)$ vector of constant terms; W is an $(n\times n)$ spatial weights matrix; ε is an $(n\times1)$ vector of error terms, which is homoscedastic, independent and normal distributed; ρ is a spatial autoregressive coefficient; β are unknown coefficients; and WY denotes the endogenous interaction effects (LeSage and Pace 2009).

Spatial error model

Spatial error model (SEM) has only the interaction effects among disturbance terms. Each observation is spatially dependent on unobservable neighboring characteristics. The model is expressed as below:

$$Y = \alpha\iota + X\beta + u \tag{9}$$

$$u = \lambda W u + \varepsilon \tag{10}$$

$$\varepsilon \sim N(0, \sigma^2 I_n) \tag{11}$$

where u is an $(n\times 1)$ vectors of error terms; λ is a spatial autocorrelation coefficient; and Wu is the interaction effects among the disturbances (LeSage and Pace 2009).

Spatial two stages least squares (S2SLS) with heteroscedasticity and autocorrelation consistent (HAC) standard errors

This method still assumes the spatial model follows a general process as:

$$Y = \rho WY + \alpha\iota + X\beta + u \tag{12}$$

$$Y = Z\gamma + u \tag{13}$$

where W is an $(n\times n)$ spatial weights matrix; $Z = (WY, \iota, X)$; and $\gamma' = (\rho, \beta', \alpha')$.

The spatial model in equation (12) suggests there is endogeneity because of the spatially lagged dependent variable WY. Dependent variable Y is correlated with the disturbances so that estimations would be biased. Endogeneity could be eliminated by a S2SLS approach. In particular, let $H = (X, WX, W^2X)$ be a non-stochastic matrix of instruments, and $\hat{Z} = PZ$ where $P = H(H'H)^{-1}H'$. The S2SLS estimates for γ are presented as below:

$$\hat{\gamma} = (\hat{Z}'\hat{Z})^{-1}\hat{Z}'Y \tag{14}$$

What's more, we relax the assumption of homoscedasticity. Disturbances may be heteroskedastic or correlated with each other. This approach considers such problem and assumes the error terms are generated as follows:

$$u = R\varepsilon \tag{15}$$

where ε is a vector of innovations satisfying (8); and R is an $(n\times n)$ non-stochastic matrix whose elements are unknown (Kelejian and Prucha 2007).

Since we allow for correlation and heteroscedasticity in the disturbance process, S2SLS with HAC estimators would be robust and asymptotically consistent (Kelejian and Prucha 2007).

Spatial weights matrix

Spatial weights matrix W is very important in spatial models. It illustrates spatial relations between n regions. Specifically, w_{ij} reflects the spatial influence of region j on region i. There are two spatial weight matrices that we discussed in this paper (Anselin 2002).

(1) k-nearest neighbor weights

According to the centroid distances from region i to other regions, we could figure out k closest regions to i, which are denoted as $N_k(i) = \{j(1), \dots, j(k)\}$. Those regions have spatial correlations with region i. The spatial weight matrix is presented as:

$$w_{ij} = \begin{cases} 1, & j \in N_k(i) \\ 0, & otherwise \end{cases}$$

(2) Radial distance weights

It is also called distance band weights. d is a bandwidth. If the spatial distance from region i to j is not more than the bandwidth, there is a direct spatial influence. This spatial weight matrix is shown as below:

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

After defining the spatial weight matrix, researchers could normalize W, which means the elements of each row sum to one.

RESULTS

Data description

Arms-length transaction data for single-family residential properties was provided by the Brookfield Real Property Solutions (RPS)[3]. Although we had access to data from previous years,

[3] RPS is the largest provider of residential real estate valuation in Canada, owned by Brookfield Asset Management. We made a Nondisclosure and Information Transfer Agreement with the company to get residential property transactions around Alberta.

we chose 2010 as our starting year in order to avoid the effects of the 2008 global financial crisis and its effects on real estate markets in North America. Figure 3 presents housing prices changes in Canada, showing the dramatic drop from 2008 to 2009.

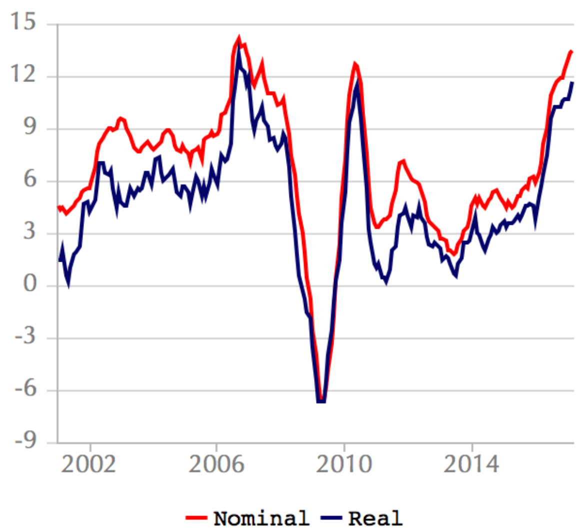

Figure 3. Housing price change in Canada[4]

After adjusting data with missing values and obviously erroneous longitude and latitude information, and choosing the recent sale prices for properties having more than one transactions, we finally arrived at a sample with 1,426 observations from 2010 to 2017. Using Alberta Consumer Price Index (CPI), sales prices were adjusted to constant 2016 Canadian dollars. Figure 4 displays spatial distribution of real property values in our study area. Houses close to Calgary have higher prices than those in the town overall.

[4] Source of the figure: Global Property Guide: https://www.globalpropertyguide.com/real-estate-house-prices/C#canada).

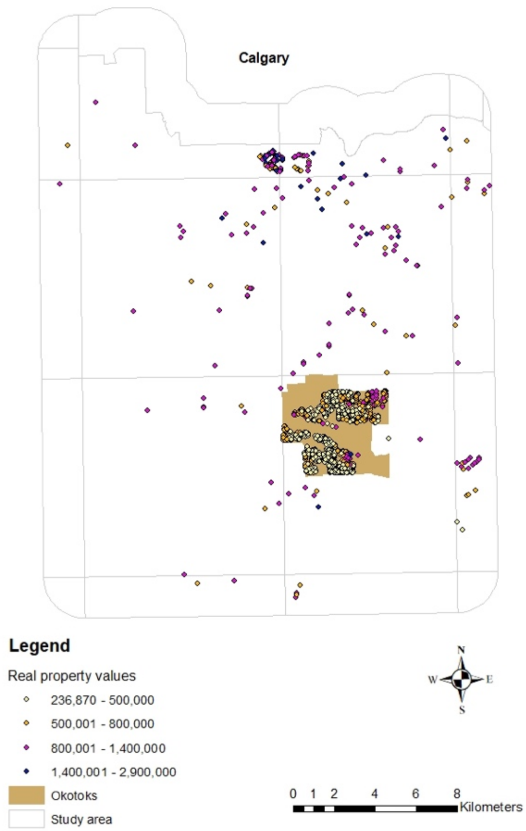

Figure 4. A map of spatial distribution of housing sales price in the study area

Regarding hedonic price model, we need data on housing characteristics in order to estimate individuals' WTP for those characteristics. These include structural, locational, neighborhood variables and environmental amenities. Table 1 summarizes all those variables that we used in this study.

Structural variables were mainly obtained from the original dataset. The original data from the Brookfield RPS includes nominal sales prices and some structural information for each property, such as the square feet of living area and lot size, number of bathrooms, bedrooms and garages, and the year that it was sold.

Locational variables were generated by ArcGIS. The City of Calgary is 18 kilometers north of the Town of Okotoks. Calgary is the third-largest city in Canada and the largest one in Alberta.

Private companies are involved in energy, agriculture, transportations and financial services. Consequently, distance to the downtown of Calgary represents the distance to an employment center[5] (Geoghegan et al. 2003). Since our sample is about a town and its surrounding rural area, the number of hospitals is limited. It is more reasonable to calculate the distance to the nearest hospital or medical clinic. Moreover, we considered proximity to nearest water features. Since water features provide scenic views and recreational opportunities, researchers believed people are willing to pay more for a house closer to water bodies (Leggett and Bockstael 2000, Bin et al. 2009).

School quality is also an important element for homebuyers. The study area belongs to the Foothills School Division No.38. Each observation is located in a specific school block. In this division, the blocks only differ in the available elementary schools. Based on average school quality scores available through the Fraser Institute[6], we found scores ranged from 5.7 to 7.16. Therefore, an elementary school with a score higher than average (6.43) was defined as high quality.

Housing prices are always influenced by their neighborhoods. People would like to buy houses in high-evaluated blocks. Having more highly educated people and higher salaries may result in higher housing prices. Neighborhoods that we had were based on the 2011 census tracts from Statistics Canada at the "Dissemination Area" (DA) level. Researchers always calculated population density by using the area of all types of lands in a neighborhood (Ihlanfeldt and Taylor 2004, Stoms et al. 2009). Considering that people only live on developed lands, density based on developed lands can better reflect the reality. Meanwhile, we adjusted the median household income to 2016 dollars by Alberta CPI. According to the value of interquartile range (IQR), income over 75th percentile in the data set was set as a high level, and that under 25th percentile was a low level. The education level in each DA also matters. Researchers figured out that the more people with college education, the higher housing prices in a neighbourhood (Geoghegan et al. 2003, Borchers and Duke 2012). In terms of the highest education, percentage of high school certificate and percentage of postsecondary certificate were included into our

[5] Distance to Calgary was generated under the road network data from CanMap Content Suite.
[6] The school quality scores were obtained through the Fraser Institute website: http://alberta.compareschoolrankings.org/elementary/SchoolsByRankLocationName.aspx.

analysis. We also assumed that employment rate in a neighborhood also affects housing prices. Employment rate captures economic conditions of a block (Cho et al. 2008).

Open spaces have potential influences on dwelling prices. Based on the 30-meter resolution land-use and land-cover raster image in 2016[7], we obtained different categories of open spaces in the study area. According to prior studies on housing prices with open spaces, we divided all open spaces into five categories: parks, forests, pastures, croplands, and other landscapes including grasslands and shrublands. Following City of Calgary (2002), we assumed that residents could easily get access to open space opportunities if such open spaces are within 450 meters or a five-minute walk from their home. Therefore we tried 100-meter, 200-meter, 300-meter and 400 meter rings within 450 meters in order to assess to evaluate the buffer within which people value open spaces. Finally we chose a 200-meter buffer as the threshold.

We also include a variable reflecting season. Since there are more property transactions in summer than other seasons due to the Canadian school schedule, we added a dummy variable for season to this study. In order to capture the time fixed effects, dummies for each year were also included.

Table 1 provides summary data for the variables included in the model. It is worth noting that the mean house price in this area was 19% higher than the mean home price in Calgary in 2017 ($504,867) (Calgary Real Estate Board 2017).

Table 1. Summary of variables

Variables	Definition	Min	Mean	Max	Std.Dev.
sale price(p)	House transaction price (2016$ CAD)	236,870	600,205	2900,000	300,078
$living$	Square feet of living space	703	1,968	6,588	651
lot	Acres of lands owned by a household	0.0086	0.5814	9.9000	1.3950
age	Age of the house	1	13.1900	110	12.2186
$cond$	1 if the condition of the house is "excellent" or "good", 0	0	0.8331	1	0.3730

[7] Data was from Agriculture Agri-Food Canada (AAFC).

	otherwise				
$base$	1 if the basement is "finished", 0 otherwise	0	0.6227	1	0.4849
$bath$	Number of bathrooms	0	2.7970	6	0.7228
bed	Number of bedrooms	1	2.8100	6	0.7339
$garage$	Number of garages	0	2.0370	5	0.7384
$calgary$	Distance to the downtown of Calgary (meters)	23,156	37,928	48,850	4,447
$hospital$	Distance to nearest hospital or clinic (meters)	210	3,066	15,656	2,923
$water$	Euclidean distance to nearest water feature (meters)	135	591	3,710	494
$school$	1 if the quality index of elementary school in public school neighborhood is greater than 6.43, 0 otherwise	0	0.5428	1	0.4983
$density$	Population/acres of developed lands in each DA	0.3843	9.5741	18.3768	4.8443
$income\_high$	1 if the median household income is greater than 149,030.73 in each DA, 0 otherwise (2016 $CAD)	0	0.0470	1	0.2117
$income\_low$	1 if the median household income is less than 79,979.56 in each DA, 0 otherwise (2016 $CAD)	0	0.0750	1	0.2635
$high$	Percentage of people aged 15 years old or over with high school certificate or equivalent in each DA	0.1829	0.2816	0.6200	0.0558
$post$	Percentage of people aged 15 years old or over with postsecondary certificate in each DA	0.2400	0.5748	0.6525	0.0611
$employ$	Employment rate of people aged 15 years old or over in each DA	0.5280	0.7230	0.8690	0.0553
$pasture\_2$	Acres of pastures within a 200-meter buffer	0	0.0507	4.5322	0.2924
$crop\_2$	Acres of croplands within a 200-meter buffer	0	0.9166	22.1362	2.6009
$other\_2$	Acres of grasslands or shrublands within a 200-meter buffer	0	2.5083	23.6633	4.5041
$forest\_2$	Acres of forests within a 200-	0	0.3211	10.2724	0.9603

	meter buffer				
$park\_2$	Acres of parks within a 200-meter buffer	0	3.5061	18.3504	3.5149
$season$	1 if the house is sold between April and September, 0 otherwise	0	0.5947	1	0.4911
N		1426			

Model specification

It is important to choose an appropriate functional form for the estimation. In order to figure out which functional form is more fit, we ran OLS estimations based on four different functional forms in Table 2. Comparing R^2 and adjusted R^2, as well as following prior studies, we chose the double log functional form to have the best fit (Tyrvainen 2000, Atreya et al. 2013). The hedonic pricing model is defined as:

$$\ln\,(P_{it}) = \beta_0 + \boldsymbol{\beta}_1'\ln\boldsymbol{S}_{1it} + \boldsymbol{\beta}_2'\boldsymbol{S}_{2it} + \boldsymbol{\beta}_3'\ln\boldsymbol{L}_{it} + \boldsymbol{\beta}_4'\boldsymbol{N}_{it} + \boldsymbol{\beta}_5'\boldsymbol{E}_{it} + \theta_t + \varepsilon_{it} \qquad (16)$$

where $\boldsymbol{S}_{1it}$ is a vector of continuous structural variables and $\boldsymbol{S}_{2it}$ is a vector of discrete structural variables; and θ_t denotes time fixed effects.

Table 2. Results of four different functional forms

Functional form	R^2	Adjusted R^2
Linear	0.8211	0.8171
Double log	0.8746	0.8719
Log linear	0.8660	0.8630
Linear log	0.7756	0.7706

Diagnostic tests

Since all observations are spatially distributed, they may be correlated with each other. Following the literature, we used the Moran's I test to check whether spatial dependence is present or not (Paterson and Boyle 2002).

In terms of the spatial extent of all observations, we found that the 2-nearest neighborhoods are reasonable thresholds for the spatial weight matrix. Moran's I test in Table 3 identified that spatial autocorrelation does indeed exist. Moreover, the Lagrange Multiplier (LM) test was used to choose between SLM and SEM (Mei et al. 2017). Table 4 suggested that the SLM model is better because its LM statistic is much larger than SEM.

Table 3. Moran's I test

Moran's I statistic	Standard deviate	*P*-value
0.2180	9.4382	2.2e-16

Table 4. LM tests for spatial dependence

	Statistic	*P*-value
LM spatial lag	96.462	2.2e-16
LM spatial error	82.36	2.2e-16
Robust LM spatial lag	25.723	3.94e-07
Robust LM spatial error	11.621	0.000652

Results without DID variable

We began by estimating the model using OLS, SLM and S2SLS with HAC estimators without accounting for the policy treatment. Results of OLS and SLM are shown in Table 5 and Table 6 respectively. Meanwhile, a S2SLS with HAC estimators was included to get asymptotically consistent estimations in Table 7.

Without considering spatial dependence, OLS estimation may be inefficient. Most importantly, the assumption of independence of observations implies that parameters could be used directly to illustrate the effect of explanatory variables on the dependent variable, that is $\frac{\partial y_i}{\partial x_{ir}} = \beta_r$ and $\frac{\partial y_i}{\partial x_{jr}} = 0$ for $j \neq i$ and all variables r.

However, interpretation becomes complicated if the model contains spatial lags of the dependent variable (LeSage and Pace 2009). We took SLM model in equation (7) as an example.

$$V(W) = (I_n - \rho W)^{-1} = I_n + \rho W + \rho^2 W^2 + \rho^3 W^3 + \cdots \tag{17}$$

$$Y = V(W)(X\beta + \alpha\iota + \varepsilon) \tag{18}$$

where $V(W) = \begin{pmatrix} V_{11} & \cdots & V_{1n} \\ \vdots & \ddots & \vdots \\ V_{n1} & \cdots & V_{nn} \end{pmatrix}$.

Now for each variable r, we have $\frac{\partial y_i}{\partial x_{ir}} = V_{ii}\beta_r$, and $\frac{\partial y_i}{\partial x_{jr}} = V_{ij}\beta_r$. A change in an independent variable for a region may influence the dependent variables in all other regions. Therefore, there are three different measures of impact.

(1) The average direct impact: average changes in i region arising from changes of x_{ir};
(2) The average indirect impacts: average changes over all other regions arising from changes of x_{ir}. It is also called spatial spillover effects;
(3) The average total impacts: average changes over all n regions arising from changes of x_{ir}.

All models considered time fixed effects. Comparing those three models, we found all structural and locational variables included have significant effects on housing prices. One of neighbourhood characteristics, $density$, is significantly negative in all models. Regarding open space variables, $pasture\_2$ and $forest\_2$ are significantly positive. $season$ also has positive effects on housing prices. SLM and S2SLS suggest that the spatial autoregressive coefficient is significantly less than 0.2.

As mentioned before, results of S2SLS with HAC estimators are asymptotically consistent, so all interpretations are based on Table 7. In terms of structural characteristics, an increase of 1% square feet of living area for a property raises its own price by 0.6842%, as well as all other property prices in our study area by 0.1127%. The larger the lot size and the more garages on a property, the higher its price and other dwelling prices. For $cond$ and $base$ dummies, a property with an "excellent" or "good" condition, as well as a finished basement will increase all property prices. Significantly negative direct, indirect and total impacts of age imply that as a house gets old, its own price and other property prices would decline. All impacts of $bath$ and bed are significantly negative, which suggest that holding the area of residence constant, increasing numbers of bathroom or numbers of bedroom would reduce areas for each bathroom or bedroom. In this case, housing prices decrease (No Kim et al. 2016).

If a property is located 1% meters further away from the downtown of Calgary, its own price declines by 0.3205%, and all other property prices would be also reduced by 0.0524%. People want to live close to the city of Calgary due to the convenience of work. Distances to hospital have significantly positive influences on housing prices. That a house close to a hospital or a medical clinic has a lower price may be because of concern about traffic volumes. Meanwhile, people value water. In close proximity to water bodies, a property has a higher price, which also raises other dwelling prices. This is because of the recreational and aesthetic values of water (Jr and Jones 1995).

Except for $density$, other neighborhoods attributes are not significant. Higher population density in a neighborhood decreases its housing prices as well as other housing values in other neighborhoods. Since population density could measure congestion, its effects are negative (Geoghegan et al. 2003).

Average impacts of $pasture\_2$ are significantly positive. For a property, one more acre of pastures within a 200-meter buffer raises its price by 2.78%, and it also increases other properties' prices by 0.45%. Increasing an acre of forests for a dwelling, all dwelling prices would go up by 0.98% on average. However, $park\_2$ has no effects on housing prices. Compared to parks, open spaces such as pastures and forests not only have wild views, but also could provide wildlife habitats and promote biodiversity. Since urban residents get limited accesses to those natural settings, they may be more valuable than parks.

Positive impacts of $season$ mean that if a house is sold between April and September, its price would increase, so would other housing prices.

Without considering policy effects, we found people value open spaces especially pastures and forests. Furthermore, pastures have higher values than forests.

Table 5. Results based on an OLS estimation

Variables	Coefficients	Variables	Coefficients
$\ln(living)$	0.7382^{***}	$income\_high$	0.0029

	(0.0202)		(0.0234)
ln (lot)	0.081***	$income\_low$	-0.0092
	(0.0064)		(0.0231)
age	-0.0024***	$high$	0.1248
	(5e-04)		(0.1094)
$cond$	0.0401***	$post$	-0.0273
	(0.0113)		(0.121)
$base$	0.1065***	$employ$	0.1953*
	(0.0084)		(0.1066)
$bath$	-0.0424***	$pasture\_2$	0.0267*
	(0.0074)		(0.0138)
bed	-0.0896***	$crop\_2$	-0.003*
	(0.0062)		(0.0016)
$garage$	0.0451***	$grass\_2$	2e-04
	(0.0061)		(0.0016)
ln ($calgary$)	-0.3751***	$forest\_2$	0.0116**
	(0.0453)		(0.0048)
ln ($hospital$)	0.0333***	$park\_2$	2e-04
	(0.0073)		(0.0013)
ln ($water$)	-0.0305***	$season$	0.0166**
	(0.0057)		(0.0076)
$school$	-0.003	intercept	11.8203***
	(0.0095)		(0.5546)
$density$	-0.0066***		
	(0.0012)		
Fixed effects		Y	

***, **, and * mean the coefficient is significant at 1%, 5% and 10% respectively;
Estimated coefficients followed by *t*-values in parentheses

Table 6. Results based on a SLM model

Variables	Direct Impact	Indirect Impact	Total Impact
ln ($living$)	0.6726***	0.1379***	0.8105***
	(34.0089)	(9.3351)	(32.9643)
ln (lot)	0.0774***	0.0159***	0.0932***
	(12.294)	(7.4344)	(12.1253)
age	-0.0021***	-4e-04***	-0.0025***
	(-4.6017)	(-4.2812)	(-4.6287)
$cond$	0.0393***	0.0081***	0.0474***
	(3.6076)	(3.3351)	(3.5998)
$base$	0.1047***	0.0215***	0.1262***
	(13.0833)	(7.4893)	(12.7814)
$bath$	-0.0371***	-0.0076***	-0.0448***
	(-5.1713)	(-4.5764)	(-5.1741)
bed	-0.0806***	-0.0165***	-0.0971***

	(-13.4659)	(-8.0573)	(-13.5593)
garage	0.0396***	0.0081***	0.0477***
	(6.7369)	(5.4028)	(6.6968)
ln (*calgary*)	-0.311***	-0.0637***	-0.3746***
	(-7.1207)	(-6.0715)	(-7.2158)
ln (*hospital*)	0.0203***	0.0041***	0.0245***
	(2.8016)	(2.8169)	(2.8261)
ln (*water*)	-0.0237***	-0.0049***	-0.0286***
	(-4.2579)	(-4.0462)	(-4.2915)
school	-0.0092	-0.0019	-0.0111
	(-1.0137)	(-0.9971)	(-1.0126)
density	-0.0048***	-0.001***	-0.0058***
	(-4.1282)	(-3.9854)	(-4.1675)
income_high	-0.0158	-0.0033	-0.0191
	(-0.7171)	(-0.7154)	(-0.7177)
income_low	-0.0057	-0.0011	-0.0068
	(-0.2553)	(-0.2508)	(-0.2548)
high	0.0891	0.0182	0.1073
	(0.8477)	(0.8359)	(0.847)
post	-0.0352	-0.0072	-0.0424
	(-0.3027)	(-0.2998)	(-0.3025)
employ	0.1204	0.0246	0.145
	(1.1591)	(1.1504)	(1.16)
pasture_2	0.0282**	0.0058**	0.034**
	(2.0994)	(2.0318)	(2.0978)
crop_2	-0.0024	-5e-04	-0.0029
	(-1.5582)	(-1.5197)	(-1.5561)
grass_2	-0.0016	-3e-04	-0.002
	(-1.0029)	(-0.9893)	(-1.0023)
forest_2	0.0076*	0.0016*	0.0091*
	(1.6521)	(1.6185)	(1.6518)
park_2	5e-04	1e-04	6e-04
	(0.4002)	(0.3964)	(0.4)
season	0.0157**	0.0032**	0.019**
	(2.1554)	(2.0892)	(2.1547)
Fixed effects		Y	
ρ		0.1808	

z-values are presented in parentheses

Table 7. Results based on a S2SLS with HAC estimators approach

Variables	Direct Impact	Indirect Impact	Total Impact
ln (*living*)	0.6842***	0.1127***	0.7969***
	(12.6798)	(4.9786)	(16.5851)

ln (lot)	0.0778*** (9.6964)	0.0132*** (3.0586)	0.091*** (7.6191)
age	-0.0021*** (-3.9989)	-3e-04*** (-4.1118)	-0.0025*** (-4.295)
$cond$	0.039*** (3.0613)	0.0067*** (2.05)	0.0457*** (2.9106)
$base$	0.1049*** (14.0409)	0.0175*** (4.0405)	0.1224*** (13.2392)
$bath$	-0.0382*** (-8.2306)	-0.0064*** (-3.6009)	-0.0446*** (-7.8814)
bed	-0.0824*** (-10.9152)	-0.0137*** (-3.903)	-0.0961*** (-10.4576)
$garage$	0.0403** (2.4979)	0.0072* (1.7316)	0.0474** (2.3693)
ln ($calgary$)	-0.3205*** (-6.1346)	-0.0524*** (-4.4799)	-0.3729*** (-6.7319)
ln ($hospital$)	0.0227*** (4.599)	0.0038*** (3.2803)	0.0265*** (4.6663)
ln ($water$)	-0.0247*** (-2.2606)	-0.0038*** (-2.7057)	-0.0285*** (-2.36)
$school$	-0.0078 (-0.5614)	-0.0013 (-0.5586)	-0.0091 (-0.5637)
$density$	-0.0051** (-2.6135)	-8e-04*** (-3.4237)	-0.0059*** (-2.7712)
$income\_high$	-0.0121 (-0.327)	-0.0032 (-0.4558)	-0.0153 (-0.3494)
$income\_low$	-0.0061 (-0.3735)	-0.0012 (-0.4051)	-0.0072 (-0.3799)
$high$	0.0986 (1.0112)	0.0154 (0.934)	0.114 (1.0071)
$post$	-0.0303 (-0.2384)	-0.004 (-0.1887)	-0.0343 (-0.2323)
$employ$	0.1304 (1.2649)	0.0191 (1.2256)	0.1495 (1.2729)
$pasture\_2$	0.0278* (2.0563)	0.0045* (1.9793)	0.0322** (2.0848)
$crop\_2$	-0.0025 (-1.5532)	-4e-04 (-1.6333)	-0.0029 (-1.5832)
$grass\_2$	-0.0013 (-0.9226)	-2e-04 (-0.8951)	-0.0015 (-0.924)
$forest\_2$	0.0084*** (2.8701)	0.0014** (1.9921)	0.0098*** (2.7519)
$park\_2$	5e-04 (0.5199)	1e-04 (0.4926)	6e-04 (0.5184)
$season$	0.0159*	0.0028	0.0188*

	(1.7315)	(1.4243)	(1.6943)
Fixed effects		Y	
ρ		0.1493	

Results with DID variable

In order to figure out effects of the policy change in the Town of Okotoks, we added policy treatment, and chose appropriate treatment as well as control groups.

As mentioned before, Okotoks implemented a finite policy in 1998 to keep the population 30,000-35,000 for an extended period. But in September 2012, the Okotoks town council relaxed the policy to one of continuous growth to increase the population capacity and allow more development. We assumed that it will intensify the exploitation on developable lands. As discussed before, we tried different buffers within walkable distances, and only found that people value pastures within a 200-meter buffer.

Since people value these kinds of developable lands, and the policy change opens up the possibility that these lands will be developed in the near future, the treatment group includes all properties having developable lands within a 200-meter ring of the property, while the control group contains those without developable lands in that ring. In other words, we assumed that such policy does not influence properties in the control group. The two groups are subject to the same contemporaneous influences such as macroeconomic changes in the housing market. Meanwhile, we defined developable lands includes pastures, croplands, and other lands such as grasslands and shrublands. Therefore, the DID methods capture the average effect of the policy on those properties with developable lands in a 200-meter buffer. $develop$ equals to 1 when there are developable lands in a 200-meter radius.

We needed to determine a cut-off date for the effect of the treatment. In our study, we tried different cut-off dates beginning from October 2012. Finally we chose November 2012 as the time after which residents' expectations on developable lands changed. That also means there were lags in people's expectations. So $policy$ equals to 1 if a property is sold after November 2012. Table 8 summarizes housing transactions under treatment and control groups.

Table 8. The distribution of property transactions in treatment and control groups before and after November 2012

	Pre-treatment ($policy = 0$)	Post-treatment ($policy = 1$)	Total
Treatment group ($develop = 1$)	246	962	1,208
Control group ($develop = 0$)	64	154	218
Total	310	1,116	1,426

Using log mean prices in each year, we plotted Figure 5 for treatment and control groups[8]. It is obvious that before 2013, treatment and control groups had similar trends. Differences between log mean prices of treatment and control groups decreased after 2013, which implied people's willingness to pay for developable land probably went down.

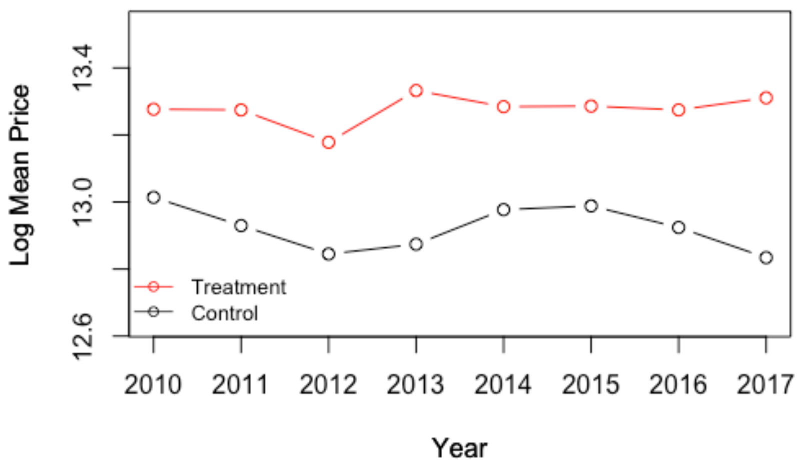

Figure 5. Log mean prices of properties sold from 2010 to 2017

The model without DID variable in equation (16) changes to:

$$\ln(P_{it}) = \beta_0 + \boldsymbol{\beta'_1}\ln\boldsymbol{S_{1it}} + \boldsymbol{\beta'_2}\boldsymbol{S_{2it}} + \boldsymbol{\beta'_3}\ln\boldsymbol{L_{it}} + \boldsymbol{\beta'_4}\boldsymbol{N_{it}} + \boldsymbol{\beta'_5}\boldsymbol{E_{it}} + \beta_6 policy_{it} + \beta_7 develop_{it} + \beta_{DID} DID_{it} + \theta_t + \varepsilon_{it} \quad (19)$$

where variable DID is the interaction of $policy$ and $develop$.

[8] Since months in which treatment groups and control groups had data were not consistent, mean prices in years were used.

According to equation (5), the coefficient $\hat{\beta}_{DID}$ indicates the casual effects of the policy change on properties with developable lands around. This DID estimator is presented as following expression:

$$\hat{\beta}_{DID} = \left(\ln\bar{P}_{treatment,policy=1} - \ln\bar{P}_{treatment,policy=0}\right) - (\ln\bar{P}_{control,policy=1} - \ln\bar{P}_{control,policy=0}) \quad (20)$$

where the bar implies the mean value of a property.

Table 9 and Table 10 are estimation results for the SLM and S2SLS models. Both models consider endogenous interactions among observations. Usually the DID method assumes that an observation's outcome is only affected by its own treatment, and there is no spillover treatment effects, which is called the Stable Unit Treatment Value Assumption (SUTVA) (Rubin 1978). However, when spatial interactions occur, the treatment could propagate through the network so that some observations would also be affected (Manski 2013, Arduini et al. 2016). Now ATE becomes the aggregation of the Average Direct Treatment Effect (ADTE) and the Average Indirect Treatment Effect (AITE). ADTE denotes the direct effects as well as feedback loop treatment effects on its own outcome by individual i's treatments, and AITE is the indirect effects of i's treatment on other observations (Arduini et al. 2016).

Compared to the SLM, the significance of $garage$ and $season$ in the S2SLS decline, but three different impacts of $crop\_2$ and $policy$ become significant.

We still take the S2SLS model in Table 10 as the model for discussion of results. Regarding the S2SLS without and with the DID variable, we figured out that except for $crop\_2$, other variables are robust. Table 10 implies one more acre of cropland within the 200-meter buffer declines all property prices by 0.32%. Although croplands could provide scenic views and wildlife habitats, there are also disamenities such as noise, dust and odors coming from pesticides or fertilizers. Impacts of $policy$ are significantly positive, which means that if a property was sold after November 2012, its own price increased and other property prices were influenced as well. in terms of $develop$, if there are developable lands within a 200-meter ring of a property, not only does its price increase, but other housing prices also increase. With respect to the DID variable, the new policy has negative effects on property prices in the treatment group. It also has negative externalities on other properties.

Table 9. Results of a SLM with DID variable

Variables	Direct Impact	Indirect Impact	Total Impact
$\ln(living)$	0.6725***	0.1363***	0.8088***
	(33.4698)	(9.2478)	(31.6168)
$\ln(lot)$	0.0778***	0.0158***	0.0935***
	(12.4229)	(7.6071)	(12.3164)
age	-0.0021***	-4e-04***	-0.0025***
	(-4.838)	(-4.5544)	(-4.8871)
$cond$	0.0376***	0.0076***	0.0453***
	(3.3984)	(3.1383)	(3.3852)
$base$	0.1054***	0.0214***	0.1268***
	(13.2833)	(7.3289)	(12.7738)
$bath$	-0.0367***	-0.0074***	-0.0442***
	(-5.1789)	(-4.544)	(-5.1721)
bed	-0.0806***	-0.0163***	-0.0969***
	(-13.2588)	(-7.8687)	(-13.2171)
$garage$	0.0392***	0.008***	0.0472***
	(6.7751)	(5.6305)	(6.7889)
$\ln(calgary)$	-0.3152***	-0.0638***	-0.379***
	(-7.1278)	(-5.8761)	(-7.16)
$\ln(hospital)$	0.0203***	0.0041***	0.0243***
	(2.813)	(2.7928)	(2.8316)
$\ln(water)$	-0.0231***	-0.0047***	-0.0278***
	(-4.2067)	(-3.9499)	(-4.2282)
$school$	-0.0103	-0.0021	-0.0124
	(-1.134)	(-1.1093)	(-1.1321)
$density$	-0.0047***	-9e-04***	-0.0056***
	(-3.8812)	(-3.7104)	(-3.9038)
$income\_high$	-0.0138	-0.0029	-0.0167
	(-0.6109)	(-0.6173)	(-0.6128)
$income\_low$	-0.0057	-0.0011	-0.0069
	(-0.251)	(-0.2429)	(-0.2498)
$high$	0.08	0.0162	0.0962
	(0.7494)	(0.7433)	(0.7495)
$post$	-0.0463	-0.0093	-0.0556
	(-0.3971)	(-0.3915)	(-0.3966)
$employ$	0.127	0.0256	0.1526
	(1.2415)	(1.2258)	(1.2415)
$pasture\_2$	0.0281**	0.0057**	0.0338**
	(2.1482)	(2.0797)	(2.1466)
$crop\_2$	-0.0026	-5e-04	-0.0031

	(-1.595)	(-1.5672)	(-1.5949)
$grass\_2$	-0.0018 (-1.1375)	-4e-04 (-1.1261)	-0.0022 (-1.1376)
$forest\_2$	0.0081* (1.7007)	0.0016* (1.6783)	0.0097* (1.7026)
$park\_2$	4e-04 (0.2915)	1e-04 (0.2945)	5e-04 (0.2923)
$season$	0.0168** (2.2656)	0.0034** (2.1885)	0.0202** (2.2636)
$policy$	0.0492 (0.9113)	0.01 (0.901)	0.0591 (0.9109)
$develop$	0.035* (1.801)	0.0071* (1.7853)	0.0421* (1.8047)
DID	-0.0375* (-1.6907)	-0.0076* (-1.6611)	-0.0451* (-1.6913)
Fixed effects		Y	
ρ		0.1790	

Table 10. Results of a S2SLS with DID variable

Variables	Direct Impact	Indirect Impact	Total Impact
ln $(living)$	0.6839*** (12.5601)	0.1092*** (5.0204)	0.7931*** (16.1353)
ln (lot)	0.0783*** (9.7612)	0.0129*** (3.1045)	0.0912*** (7.7554)
age	-0.0022*** (-4.2496)	-3e-04*** (-3.9662)	-0.0025*** (-4.5137)
$cond$	0.0375*** (2.827)	0.0063*** (1.9925)	0.0438*** (2.7161)
$base$	0.1058*** (13.6958)	0.0171*** (4.0526)	0.1229*** (12.9084)
$bath$	-0.0378*** (-8.2606)	-0.0061*** (-3.5309)	-0.0439*** (-7.7448)
bed	-0.0817*** (-10.5243)	-0.0132*** (-3.9266)	-0.0949*** (-10.1898)
$garage$	0.0399** (2.562)	0.0068* (1.7808)	0.0467** (2.436)
ln $(calgary)$	-0.3271*** (-6.3083)	-0.0519*** (-4.5478)	-0.379*** (-6.8831)
ln $(hospital)$	0.0226*** (4.3336)	0.0036*** (3.2259)	0.0262*** (4.4007)
ln $(water)$	-0.0246** (-2.1583)	-0.0036** (-2.61)	-0.0282** (-2.2478)
$school$	-0.0097	-0.0016	-0.0113

	(-0.7093)	(-0.6873)	(-0.7095)
$density$	-0.005*** (-2.5921)	-8e-04*** (-3.5051)	-0.0058*** (-2.7491)
$income\_high$	-0.0099 (-0.2791)	-0.0027 (-0.4187)	-0.0126 (-0.3018)
$income\_low$	-0.0077 (-0.4496)	-0.0015 (-0.4899)	-0.0091 (-0.4575)
$high$	0.0822 (0.8516)	0.0123 (0.7869)	0.0946 (0.8479)
$post$	-0.0488 (-0.3942)	-0.0076 (-0.3665)	-0.0564 (-0.3918)
$employ$	0.1377 (1.373)	0.0198 (1.3964)	0.1575 (1.3902)
$pasture\_2$	0.0279** (2.1377)	0.0043** (2.0345)	0.0322** (2.1654)
$crop\_2$	-0.0028* (-1.9083)	-4e-04** (-2.2011)	-0.0032* (-1.9717)
$grass\_2$	-0.0015 (-1.0175)	-3e-04 (-0.9609)	-0.0017 (-1.0157)
$forest\_2$	0.0087*** (2.8399)	0.0015** (2.0312)	0.0102*** (2.7376)
$park\_2$	2e-04 (0.2454)	4e-05 (0.1957)	3e-04 (0.2393)
$season$	0.0164* (1.7907)	0.0028 (1.452)	0.0192* (1.7486)
$policy$	0.0502** (1.9196)	0.0084* (1.6014)	0.0586* (1.8907)
$develop$	0.0378*** (3.3706)	0.006*** (3.0432)	0.0438*** (3.4689)
DID	-0.0387* (-1.9432)	-0.0058** (-2.1205)	-0.0445** (-1.9972)
Fixed effects		Y	
ρ		0.1460	

WELFARE MEASUREMENT

Transaction data only reveals the hedonic price function, but it is not a bid function for individuals. If we want to get inverse demand curves and the exact WTP for the policy, we need to know who is living in the houses as well as their characteristics (Bockstael and McConnell 2007). In our study, we want to know residents' marginal WTP for the policy as well as for open spaces. In terms of OLS approach, the marginal effect of an open space variable is shown as below:

$$MWTP_{o.o} = \frac{\partial P}{\partial x_r} P = \hat{\beta}_r P$$

where $\hat{\beta}_r$ is the estimate of variable r, P is the housing price, and $MWTP_{o.o}$ denotes a marginal WTP of an open space variable under OLS model.

Marginal effect of dummies is different from above. The percentage change in P for a discrete change in x_r from 0 to 1, should be shown as:

$$p_r = 100\left(\exp\left(\hat{\beta}_r\right) - 1\right)$$

where p_r is the percentage change of P with respect to the change of x_r (Garderen and Shah 2002).

And the marginal WTP of the dummy ($MWTP_{o.d}$) can be calculated as:

$$MWTP_{o.d} = \frac{p_r}{100} * \mathrm{P}$$

Since the SLM and S2SLS models include a spatially-lagged dependent variable, calculation of marginal effects is slightly different from that in OLS estimation. We know from equations (17) and (18) that the partial derivative of the dependent variable with respect to the explanatory variable is no longer the coefficient $\hat{\beta}_r$, but $(I_n - \hat{\rho}W)^{-1} * \hat{\beta}_r$. The spatial multiplier $(I_n - \hat{\rho}W)^{-1}$ can be simplified as $(1 - \hat{\rho})^{-1}$ (Anselin and Lozano-Gracia 2008, Atreya et al. 2013). Now marginal WTPs are presents as follows:

$$MWTP_{s.o} = (\frac{1}{1 - \hat{\rho}})\hat{\beta}_r P$$

$$MWTP_{s.d} = \left(\exp\left(\frac{1}{1 - \hat{\rho}} * \hat{\beta}_r\right) - 1\right) * P$$

where $\hat{\rho}$ is the estimate of the spatial autoregressive coefficient, $MWTP_{s.o}$ is the marginal effect for open space variables and $MWTP_{s.d}$ is for dummies.

Table 11 summarizes all coefficients of OLS, SLM and the S2SLS estimations. According to the results, we calculated the marginal WTPs for open spaces based on the sample mean of sales prices, and marginal WTP for the policy based on the average sales prices in the treatment group. Results in Table 12 vary across the estimation methods. Marginal WTPs of OLS are considerably different from SLM or the S2SLS. The S2SLS not only filters out spatial spillover effects, but also allows for a weaker assumption of disturbances, so the marginal WTPs are more accurate. Taking results of the S2SLS as an example, on average, individual households are willing to pay \$19,104 for one more acre of pasture, and \$5,974 for one more acre of forest within a 200-meter radius of their house. Most importantly, the marginal effect of the treatment is negative, which implies that the implementation of the new policy decreased prices of properties with developable lands in a 200-meter radius. A household in the treatment group is willing to accept \$27,551 for the policy change. In other words, individual residents are willing to pay \$27,551 to prevent the policy. Therefore, people would like to pay for open spaces, but would seek compensation for a change from a finite growth policy to a continuous growth policy.

Residents discount property prices due to the policy, meanwhile positive spillover effects strengthen individuals' marginal WTP for stopping the shift in policy. The continuous growth policy aims to increase the capacity of the town. More people implies more dwellings, more industries and more infrastructures. Residents who have access to nearby developable lands want to pay for keeping the original finite growth policy.

Table 11. Estimation results under different models

Variables	OLS	SLM	S2SLS
$\ln(living)$	0.7342*** (0.0204)	0.6638*** (0.0204)	0.6768*** (0.0567)
$\ln(lot)$	0.0816*** (0.0064)	0.0768*** (0.0061)	0.0777*** (0.0078)
age	-0.0024*** (5e-04)	-0.0021*** (4e-04)	-0.0021*** (5e-04)
$cond$	0.0370*** (0.0114)	0.0369*** (0.0108)	0.0371*** (0.0134)
$base$	0.1070*** (0.0084)	0.1041*** (0.008)	0.1047*** (0.0078)
$bath$	-0.0421*** (0.0074)	-0.0363*** (0.0071)	-0.0374*** (0.0046)
bed	-0.0889*** (0.0062)	-0.0795*** (0.0059)	-0.0812*** (0.0079)

$garage$	0.0448*** (0.0061)	0.0388*** (0.0058)	0.0399** (0.0157)
ln ($calgary$)	-0.3800*** (0.0454)	-0.3095*** (0.0438)	-0.3224*** (0.0511)
ln ($hospital$)	0.0328*** (0.0073)	0.0201*** (0.0071)	0.0224*** (0.0052)
ln ($water$)	-0.029*** (0.0057)	-0.023*** (0.0055)	-0.0241** (0.0115)
$school$	-0.0044 (0.0095)	-0.0101 (0.009)	-0.0091 (0.0137)
$density$	-0.0064*** (0.0013)	-0.0046*** (0.0012)	-0.005** (0.002)
$income\_high$	0.0051 (0.0234)	-0.0138 (0.0223)	-0.0103 (0.0351)
$income\_low$	-0.0141 (0.0234)	-0.007 (0.0221)	-0.0083 (0.0167)
$high$	0.1085 (0.1096)	0.0807 (0.1041)	0.0858 (0.0965)
$post$	-0.0624 (0.1231)	-0.0451 (0.1169)	-0.0483 (0.121)
$employ$	0.1989* (0.1065)	0.1225 (0.1015)	0.1366 (0.0986)
$pasture\_2$	0.0271** (0.0137)	0.0276** (0.013)	0.0275** (0.0135)
$crop\_2$	-0.0035** (0.0017)	-0.0026 (0.0016)	-0.0028* (0.0014)
$grass\_2$	-2e-04 (0.0017)	-0.0018 (0.0016)	-0.0015 (0.0014)
$forest\_2$	0.0119** (0.0048)	0.0079* (0.0046)	0.0086*** (0.003)
$park\_2$	-2e-04 (0.0013)	4e-04 (0.0013)	3e-04 (0.001)
$season$	0.0177** (0.0076)	0.0165** (0.0073)	0.0167* (0.0092)
$policy$	0.0480 (0.0577)	0.0496 (0.0548)	0.0493* (0.0259)
$develop$	0.0508** (0.0205)	0.0346* (0.0196)	0.0376*** (0.0114)
DID	-0.0416* (0.0234)	-0.0372* (0.0222)	-0.038* (0.0203)
Intercept	11.8790*** (0.5590)	9.379*** (0.5904)	9.8389*** (0.7628)
Fixed effects		Y	
ρ	-	0.1790	0.1460

Estimated coefficients followed by standard errors in parentheses

Table 12. Marginal WTPs under different models

	OLS	SLM	S2SLS
pasture	16,265.5555	20,177.4154	19,103.7471
forest	7,142.4395	5,775.4196	5,974.2627
treatment	-25,794.7133	-28,043.8249	-27,551.0814

CONCLUSION

The study used the Alberta town of Okotoks as a natural experiment to identify causal effects of urban development policy on property values. The DID method was performed under a hedonic price framework. After diagnostic tests, we performed a spatial lag model and a spatial two stages least squares, so direct impacts as well as spillover impacts were both revealed. Models without DID variable implied that people value pastures and forests in a 200-meter buffer. For a property, acres of pastures and forests around it have significantly positive effects on its own price, and also have significantly positive effects on other property values. With respect to models with the DID variable, the new policy has negative effects on property prices in the treatment group. It also has negative externalities on other properties. Marginal WTPs for pastures, forests and the policy were calculated using the spatial multiplier. People value pastures more than forests, but disvalue the policy. In our study area, the WTP for one more acre of pastures is $19,104 CAD, and for one more acre of forests is $5,974 CAD. Meanwhile, individual is willing to pay $27,551 CAD to avoid the continuous growth policy. In other words, people are willing to be compensated.

This study contributes to literatures discussing WTP for land-use policies. Instead of preservation policies, we focused on a policy promoting urban development. What's more, DID and spatial effects were combined. We not only considered a spatial lag model, but also a S2SLS. Compared to the spatial lag model, estimators of S2SLS are asymptotically consistent. Further studies need to choose more appropriate treatment and control groups, to improve the empirical outcomes. Moreover, except for the effects on housing prices, we could also discuss the impacts of such policy on WTP for open spaces, under a quasi-experiment framework.

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