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A spatial Difference-in-Differences estimator to evaluate the effect of change in public mass transit systems on house prices

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ABSTRACT

Evaluating the impact of public mass transit systems on real-estate values is an important application of the hedonic price model (HPM). Recently, a mathematical transformation of this approach has been proposed to account for the potential omission of latent spatial variables that may overestimate the impact of accessibility to mass transit systems on values. The development of a Difference-in-Differences (DID) estimator, based on the repeat-sales approach, is a move in the right direction. However, such an estimator neglects the possibility that specification of the price equation may follow a spatial autoregressive process with respect to the dependent variable. The objective of this paper is to propose a spatial Difference-in-Differences (SDID) estimator accounting for possible spatial spillover effects. Particular emphasis is placed on the development of a suitable weights matrix accounting for spatial links between observations. Finally, an empirical application of the SDID estimator based on the development of a new commuter rail transit system for the suburban agglomeration of Montréal (Canada) is presented and compared to the usual DID estimator.

1. Introduction

There is an important interest in the literature for establishing the willingness-to-pay (WTP) for being located close to a public mass transit (PMT) system. The transit-oriented development (TOD) concept is a good example of such a concern (Ma and Lo, 2013) and some endeavor has been devoted to explicitly include it in the modeling process (Li et al., 2012). The WTP can be assessed through either a stated preference (SP) or revealed preference (RP) approach (Hensher, 2010).[1] In empirical applications, the RP method is less common than the SP approach since data is usually difficult to collect (Peer et al., 2013). The hedonic price method applied on real estate transactions is a good example of how the RP approach may be implemented for evaluating the impact of proximity to PMT on house prices.

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[1] There is a special issue of Transportation Research Part B published in 2010 (Volume 44, Issue 6) that addresses this topic.

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Hedonic pricing model (HPM) applications have evaluated the effect of accessibility to PMT systems on single family house values (Des Rosiers et al., 2010; McMillen and McDonald, 2004), multifamily house values (Celik and Yankaya, 2006), apartment rent (Pan and Zhang, 2008; Cao and Hough, 2007), office rent (Ryan, 2005; Weinberger, 2001), industrial plant (Cervero and Duncan, 2002), and vacant land prices (Knaap et al., 2001).

The magnitude of the estimated effect is not homogenous and may depend on the type of public transportation as well as on the structure of the city (Mohammad et al., 2013; Debrezion et al., 2007, 2011). However, the interpretation of the PMT mode on real estate prices may be biased if the spatial amenities influencing the price determination process are not accounted for and are revealed to be largely correlated with the proximity of PMT. This explains why emphasis has recently been placed on the development of a Difference-in-Differences (DID) estimator to isolate the effect of PMT on house prices. Such an approach is based on a comparison of the difference in the prices of houses sold before and after the implementation of a PMT system and appears to be one of the best ways to evaluate the effect in the medium to long term (Wardrip, 2011; Gibbons and Machin, 2008).[2]

The Difference-in-Differences (DID) approach adequately controls for the possible omission of significant variables correlated with the PMT service descriptors. The DID estimator is also a convenient way to deal with the omission of a latent constant spatial structure uncorrelated with the independent variables and generating spatial autocorrelation among residuals (Dubé and Legros, 2013b, 2011). What is less clear, however, is what happens if spatial autocorrelation is generated by an autoregressive process over the dependent variable.

Many authors argue that the spatial autoregressive model (SAR) is preferable to the spatial error model (SEM) since it allows us to decompose the marginal effect into a direct and an indirect (spatial spillover) effect (Debarsy et al., 2012; LeSage and Pace, 2009). Taking advantage of this, LeSage and Pace (2009) showed that the SEM model can be transformed into a spatial Durbin version (Le Gallo, 2002; Elhorst, 2010) which is, to some extent, a natural extension of the SAR model (see also Elhorst, 2012).

This paper aims at developing a spatial Difference-in-Differences (SDID) estimator that allows for spatial autoregressive specification of the dependent variable. Based on the SAR specification of the hedonic price equation, a new estimator is proposed. The DID and SDID estimators are compared as part of a case study related to the Montréal (Canada) suburban commuter train. It shows how the SDID estimator may be preferable by allowing the marginal effect to be decomposed into two different components, while its advantage largely relies on the amplitude of the spatial autoregressive parameter estimated.

The paper is divided into five sections. The first proposes a brief review of the usual hedonic pricing model (HPM) and its extension to deal with the spatial considerations. The second section presents the DID estimator as well as its natural extension to the spatial case (SDID). Particular attention is paid to presenting the advantages of such approaches as well as the assumptions underlying these estimators. The third section propose a general discussion on the construction of the weights matrix for both models (spatial HPM and SDID) to make sure that modelers correctly measure the spatial spillover effect when data consist of real-estate transactions collected over time. This is necessary in order to avoid spurious spatial relation with respect to other temporal aspects such as perfect anticipation (Dubé and Legros, 2013a, 2011). The fourth section presents the statistics related to the development of a new Commuter Rail Train (CRT) on the northern suburban part of Montréal (Canada) and to the transaction data available to evaluate the effect of the implementation of a new PMT service. The DID and SDID estimators are applied to this case study and the results of the study are discussed and compared. The final section concludes the paper.

2. The hedonic pricing model

Hedonic theory (Rosen, 1974) states that the price of a complex good can be expressed as a function of its various extrinsic and intrinsic attributes, and that coefficients related to one specific characteristic represent its implicit (hedonic) price.

Statistically, the hedonic pricing model expresses the selling price of a complex good i sold at time t, $\mathbf{y}_{it}$, as a function of the various attributes of the good, summarized in a matrix of explanatory variables, $\mathbf{X}_{it}$, which includes a series of continuous descriptors (such as age, living area, and so on) as well as a series of dichotomous variables (presence/absence of housing attributes), a set of dummy time-variables, $\mathbf{D}_{it}$, representing time fixed effects controlling for differences in the composition of the sample in each time period (Wooldridge, 2000) as well as for temporal heterogeneity (Eq. (1)) vector of constant term, $\imath$.

$$\mathbf{y}_{it} = \imath\alpha + \mathbf{D}_{it}\delta + \mathbf{X}_{it}\beta + \epsilon_{it} \quad \forall\ i = 1, \ldots, N_T \tag{1}$$

A particularity of real-estate data used to estimate the model is that they are not strictly spatial and are clearly different from panel data (see Parent and LeSage, 2010). Transactions database consist of a set of cross-sectional data pooled over time: observations are collected over time, but individual sales are not systematically repeated in each time period. Recurrences of house sales are usually treated as random events. In such situations, the total number of observations is noted $N_T = \sum_{t=1}^{T} N_t$, where N_t is the total number of observations in one time period, t.

Thus, the vector $\mathbf{y}_{it}$ is of dimension $(N_T \times 1)$, the vector $\imath$ is of dimension $(N_T \times 1)$, the matrix $\mathbf{D}_{it}$ is of dimension $(N_T \times (T-1))$, the matrix $\mathbf{X}_{it}$ is of dimension $(N_T \times K)$, where K is the total number of independent variables, and the vector

[2] Mokhtarian and Cao (2008) propose is similar conclusion.

of error terms, ϵ_{it}, is of dimension $(N_T \times 1)$. The vectors of parameters δ and β are, respectively, of dimensions $((T-1) \times 1)$ and $(K \times 1)$, and the parameter α is a scalar. The vector β represents the implicit, or hedonic, price of the amenities, while the vector δ can be used to build a general price index related to the change in sale prices over time.[3]

In such a case, it is possible to retrieve the effect of a (marginal) change of a given independent variable on the dependent variable by taking the partial derivative of the price equation relative to the independent variables (Eq. (2)).

$$\frac{\partial \mathbf{y}_{it}}{\partial \mathbf{X}_{kit}} = \beta_k \tag{2}$$

Since it is common to express the dependent variable, $\mathbf{y}_{it}$, as the logarithmic transformation of the sale price of a house, so as to obtain a normal distribution of the dependent variable, the interpretation of the marginal effect depends on the form of the independent variable.[4] If the continuous descriptors are also expressed as a logarithmic transformation of the variable, then the β_k parameter can be interpreted as a measure of elasticity. If the dependent variable is a dummy variable, then the marginal effect of a change in the amenities on house prices is obtained using the exponential of the coefficients $(e^{\beta_k} - 1)$.

It is now widely accepted, in HPM applications, that a proportion of the unexplained variance of the price determination may be related to a spatial component (Anselin and Can, 1986; Dubin and Sung, 1987; Can, 1992; Dubin, 1998). Given that the remaining spatial autocorrelation needs to be controlled for, it is common practice to consider the spatial autoregressive (SAR) specification of the HPM to account for possible spatial spillover effect in price determination process (Eq. (3)).

$$\mathbf{y}_{it} = \mathbf{W}\mathbf{y}_{it}\rho + \imath\alpha + \mathbf{D}_{it}\delta + \mathbf{X}_{it}\beta + \epsilon_{it} \quad \forall\ i = 1, \ldots, N_T \tag{3}$$

In this specification, $\mathbf{W}$ is a spatial weights matrix summarizing the spatial relations among the observations of dimension $(N_T \times N_T)$. This matrix contains the spatial relations among observations that express the first law of geography (Tobler, 1970) stating that everything is related to everything else, but closer things more so. Some recent developments have shown how it is possible to adequately express possible spatial relations among observations while accounting for the temporal causality when dealing with cross-sectional data pooled over time (Smith and Wu, 2009; Huang et al., 2010; Dubé and Legros, 2013a,b). Isolating the spatial relations in the weights matrix makes the variable $\mathbf{W}\mathbf{y}_{it}$, of dimension $(N_T \times 1)$, expresses the mean price of houses sold in the vicinity, while the ρ (scalar) coefficient measures the spillover effect, or how price determination in the neighborhood influences the current price determination.

With the SAR specification, the calculation of the marginal effect takes into account the spatial spillover effect of the dependent variable through the form of the weights matrix as well as the amplitude of the spatial autoregressive coefficient. The marginal effect expresses the impact of a change in an independent variable on the dependent variable, as well as the feedback loops expressing the effect of a change in a given dependent variable, y_{it}, on the neighboring dependent variable, y_{jt}, and so on. Eventually, the marginal effect expresses the final result reflecting the simultaneous dependence system that leads to a new steady state equilibrium (Eq. (4)).

$$\frac{\partial \mathbf{y}_{it}}{\partial \mathbf{X}_{kit}} = (\mathbf{I} - \mathbf{W}\rho)^{-1}\mathbf{I}\beta_k \tag{4}$$

The spatial multiplier, $(\mathbf{I} - \mathbf{W}\rho)^{-1}$, can be decomposed into its infinite expansion (Eq. (5)) and can be used as an approximation based on traces of the powers of $\mathbf{W}$ since it is computationally inefficient to calculate $(\mathbf{I} - \mathbf{W}\rho)^{-1}$ when the total number of observations (N_T) is fairly large (LeSage and Pace, 2009).

$$V(\mathbf{W}) = (\mathbf{I} - \mathbf{W}\rho)^{-1} = \mathbf{I} + \mathbf{W}\rho + \mathbf{W}^2\rho^2 + \mathbf{W}^3\rho^3 + \cdots \tag{5}$$

where $\mathbf{I}$ is the identity matrix of dimensions $(N_T \times N_T)$.

The marginal effect can be split into three different components: (i) the direct marginal effect, measured by the mean of the elements appearing on the principal diagonal of $V(\mathbf{W})$ (Eq. (6)); (ii) the total marginal effect, as measured by the mean of the sum across the rows (total impact of an observation), or by the sum across the columns (total impact of an observation) of the matrix $V(\mathbf{W})$ (Eq. (7)); and (iii) the indirect marginal effect, the difference between the total marginal effect and the direct marginal effect (Eq. (8)).

$$\overline{M}_{direct} = N_T^{-1}\mathrm{trace}(V(\mathbf{W})\mathbf{I}\beta_k) \tag{6}$$

$$\overline{M}_{total} = N_T^{-1}\imath' V(\mathbf{W})\mathbf{I}\beta_k\imath \tag{7}$$

$$\overline{M}_{indirect} = \overline{M}_{total} - \overline{M}_{direct} \tag{8}$$

Since the elements on the principal diagonal of the matrix $V(\mathbf{W})$ are not necessarily equal to one, the trace of the matrix, $\mathrm{trace}(V(\mathbf{W})\mathbf{I}\beta_k)$, is different from $N_T\beta$ and thus the direct marginal effect is no longer equal to the parameter β_k. If the matrix $\mathbf{W}$ is row-stochastic, that is row-standardized, the expression of the total marginal effect on house prices can be simplified and written as $(1-\rho)^{-1}\beta_k$, when the independent variable is introduced using a logarithmic transformation, or by $e^{(1-\rho)^{-1}\beta_k}$, when the independent variable consists of a dummy variable or a non-transformed variable (Steimetz, 2010).

[3] The first time period is usually excluded from the list of independent variables and is the period of reference: all the coefficients related to the dummy variables identifying the period of the sale need to be interpreted with respect to this period of reference.

[4] The log–log functional form is one of the most used in hedonic applications.

The interpretation of the coefficients is wealthier in the SAR specification of the HPM, while the estimated coefficient using the a-spatial HPM specification can be interpreted as the marginal effect on house prices if and only if the ρ coefficient is equal to zero (or non-significant). Moreover, when the ρ coefficient is significant, the coefficients estimated using the ordinary least square (OLS) method may be biased and the estimated variance non-efficient, invalidating all the usual statistical tests, such as the t-test and the F-test (Griffith, 2005; LeSage and Pace, 2009) . Thus, there can be a real problem interpreting conclusions from the usual HPM (Eq. (2)) if spatial autocorrelation is detected among the residuals of the HPM (Eq. (1)) and if such a pattern is generated by a spatial autoregressive process of the dependent variable. Given these considerations, it is easy to see why the SAR specification has gained interest among HPM developers.

3. The Difference-in-Differences (DID) estimators

Even accounting explicitly for spatial autocorrelation of the dependent variable in the HPM, the difficulty with the hedonic approach is to ensure that all the significant variables influencing the price determination process are taken into account. Since the list of such potential variables is long, it is almost impossible to be sure that all variables are considered, even when controlling for remaining spatial autocorrelation. For this reason, it can be useful to adopt the alternative way to isolate the effect of some independent variables on the price determination process (Eqs. (1) and (3)).

According to Gibbons and Machin (2008), the Difference-in-Differences (DID) estimator approach is an efficient spatio-temporal framework within which to evaluate the impact of changing amenities over time while controlling adequately for spatial amenities that remain fixed over time. By this approach, the dependent variable is seen as the result of a "quasi-experiment" since the changes in the spatial amenities, which stem from a public decision, are clearly exogenous to buyers and sellers (Card, 1990; Card and Krueger, 1994; Meyer et al., 1995).

The DID estimator allows to compare the effect of an exogenous change on the dependent variable by comparing the difference in the level of this variable before and after a given critical date, noted t^*, between a treatment group, the group that experienced a change of the environmental amenities and a control group, which does not experience any change. The difference in behavior within the group before and after the change may then represent the net impact of the exogenous change in the environmental amenities on house prices.

The DID estimator has the advantage of eliminating the problem related to the omission of important variables that are constant over time, and some possible problems related to the functional form (McMillen, 2010). Moreover, the DID estimator allows to control adequately for the remaining spatial autocorrelation among the error terms when it is not correlated with the independent variables (Dubé et al., 2013, 2011a). In the HPM context, the DID estimator is a simple extension of the well known repeat-sales (RS) approach (Bailey et al., 1963) used to develop a general price index of the evolution of real estate.

The DID specification is attractive considering its advantages over the usual HPM approach. However, researchers must be aware that the validity of the DID estimator for the HPM is based on three important assumptions. The first is that the coefficients, reflecting preferences, are constant over time (Case and Shiller, 1987, 1989). The second one is that if no specific information is available documenting the possible changes in amenities, it is assumed that they remain constant over time (Dubé et al., 2011c). The third assumption is that even if a sale occurs more than once over time, the frequency of observations follows a random process and is not attributable to any specific characteristic that would make that property prone to frequent resales (Steele and Goy, 1997; Gatzlaff and Haurin, 1997, 1998). In other words, the sub-sample used remains representative of the real-estate stock (Clapp et al., 1991) while being smaller than in the HPM application.

3.1. The a-spatial DID

Concretely, the Difference-in-Differences (DID) estimator is based on a mathematical transformation of the HPM (Eq. (1)). The DID estimator consists of a first difference mathematical transformation occurring between the hedonic price equation for the second sale of a house (or resale, subscript r) and the hedonic price equation of the first sale (or sale, subscript s) (Eq. (9)). Since not all transactions appear at least twice in the total sample, the sub-sample for the DID estimator is reduced to n_T, where $n_T = \sum_{t=1}^{T} n_t$ and $n_t \leqslant N_t$.[5]

$$(\mathbf{y}_{ir} - \mathbf{y}_{is}) = (\iota\alpha - \iota\alpha) + (\mathbf{D}_{ir}\delta - \mathbf{D}_{is}\delta) + (\mathbf{X}_{ir}\beta - \mathbf{X}_{is}\beta) + (\epsilon_{ir} - \epsilon_{is}) \tag{9}$$

Hence:

$$\Delta\mathbf{y}_{irs} = \Delta\mathbf{D}_{irs}\delta + \Delta\mathbf{X}_{irs}\beta + \Delta\epsilon_{irs} \tag{10}$$

where $\Delta\mathbf{y}_{irs}$ is the vector of the dependent variable of dimension $(n_T \times 1)$, $\Delta\mathbf{D}_{irs}$ is a matrix indicating the time of the sale (-1) and the resale (1) of dimension $(n_T \times (T-1))$, $\Delta\mathbf{X}_{irs}$ is a matrix of explanatory variables subject to change over time of dimension $(n_T \times K^*)$, and $\Delta\epsilon_{irs}$ is a new error term of dimension $(n_T \times 1)$. The vector of parameters β is of dimension $(K^* \times 1)$ and measures the hedonic (or implicit) price pertaining to the K^* characteristics that changes over time. It should

[5] By convention, the total sample size in the repeated sales approach, n_T, is equal to a fraction of the total sample of houses sold, qN_T, where q takes a positive value less than 1. The proportion of the transactions available for the estimation is usually positively related to the temporal dimension, T, or the total number of periods.

be noted that since some characteristics are constant over time, $K^* \leqslant K$. Finally, the vector δ remains of dimension $((T-1)\times 1)$ and expresses the change in the nominal price over time (general price index). Given the mathematical transformation, the model (Eq. (9)) has no constant term.

Since the price is expressed using a logarithmic transformation, the vector of the dependent variable, $\Delta \mathbf{y}_{irs}$, represents an approximation of the growth in house prices between sale and resale. Although the interpretation of the dependent variable changes, the parameters may still be interpreted as before in the HPM. However, since the DID approach relies on isolating the effect of the independent variables (or amenities) that change over time, it is inefficient to retrieve the other marginal effects on the price level.

Using the DID specification (Eq. (9)), the parameters can also been interpreted as the impact of a change in the independent variables (or amenities) on the rise of house prices. These variations are expressed by the marginal derivative of the dependent variable with respect to the change in the independent variables that vary over time (Eq. (11)).

$$\frac{\partial \Delta \mathbf{y}_{irs}}{\partial \Delta \mathbf{X}_{k^* irs}} = \beta_{k^*} \tag{11}$$

Thus, the parameters estimated in the DID approach allow for both interpretations: (i) measuring the implicit (hedonic) price of a given amenity on the house price determination process; and (ii) measuring the effect of a change in a given amenity on the growth of house prices. For those reasons, the DID estimator is useful for assessing policy implications related to changes in some amenities, while adequately controlling, under some assumptions, for many weaknesses related to the HPM approach. The change in the characteristics usually reflects changes in environmental amenities, such as public transportation supply (Rodriguez and Mojica, 2009; Dubé et al., 2011a).

As mentioned, this approach helps avoid problems arising from the omission of significant variables in the HPM, but still produces bias in the estimated coefficients if the data generating process of the HPM is based on an autoregressive specification of the dependent variable (Eq. (3)). Thus, a simple extension of this estimator to the spatial case should account for the spatial autoregressive specification.

3.2. The spatial DID (SDID)

By taking the first difference of the spatial autoregressive specification of the hedonic price model (Eq. (3)), we obtain a spatial Difference-in-Differences (SDID) estimator. This transformation can change the interpretation of the marginal effects related to the characteristics when the changes in the amenities are not strictly pecuniary (Small and Steimetz, 2012) since it introduce spatial spillover effects through the spatial multiplier. The SDID using the SAR specification is obtained with the Eq. (12).

$$(\mathbf{y}_{ir} - \mathbf{y}_{is}) = (\imath\alpha - \imath\alpha) + (\mathbf{W}\mathbf{y}_{ir}\rho - \mathbf{W}\mathbf{y}_{is}\rho) + (\mathbf{D}_{ir}\delta - \mathbf{D}_{is}\delta) + (\mathbf{X}_{ir}\beta - \mathbf{X}_{is}\beta) + (\epsilon_{ir} - \epsilon_{is}) \tag{12}$$

Hence:

$$\Delta \mathbf{y}_{irs} = \mathbf{W}\Delta \mathbf{y}_{irs}\rho + \Delta \mathbf{D}_{irs}\delta + \Delta \mathbf{X}_{irs}\beta + \Delta\epsilon_{irs} \tag{13}$$

where the vectors $\Delta \mathbf{y}_{irs}$ and $\Delta\epsilon_{irs}$ and the matrices $\Delta \mathbf{D}_{irs}$ and $\Delta \mathbf{X}_{irs}$ have the same dimension as earlier. The vector of error terms, $\Delta\epsilon_{irs}$, is also assumed to be uncorrelated over space.

Thus, the SDID specification expresses the growth of the sale price for a given house as a function of the time-period (quarter) in which the sales were made, of the changes in the amenities (continuous and dichotomic variables) of the house between sale and resale, as well as mean growth of sale prices of houses in the neighborhood. The vector $\mathbf{W}\Delta \mathbf{y}_{irs}$, of dimension $(n_T \times 1)$, represents the mean growth of the prices of houses sold in the vicinity and allows to capture the effect of the mean growth of the sale prices of houses in the neighborhood on a given growth in price of a house after controlling for the time of the sales. The mean growth of sale prices of houses in the neighborhood is obtained by multiplying a (spatio-temporal) weights matrix, $\mathbf{W}$ of dimension $(n_T \times n_T)$, by the vector of the dependent variable, $\Delta \mathbf{y}_{irs}$ of dimension $(n_T \times 1)$.[6]

The SDID estimator allows to isolate the effect of an exogenous change in environmental (or extrinsic) amenities of the real estate, while adequately controlling for the possible spatial autocorrelation process over the dependent variable, as well as controlling for potential omission of latent constant spatial variables uncorrelated with the independent variables.

As is the case with the DID approach, the interpretation of the SDID results depends on the specification used for inferences (Eq. (3) or Eq. (12)), and thus the interpretation of the dependent variable. The calculation of the total marginal effect in the SDID specification is different than the case of the DID specification, while being similar to the SAR specification of the HPM since it takes into account the spatial multiplier (Eq. (14)).

$$\frac{\partial \Delta \mathbf{y}_{irs}}{\partial \Delta \mathbf{X}_{k^* irs}} = (\mathbf{I} - \mathbf{W}\rho)^{-1}\mathbf{I}\beta_{k^*} \tag{14}$$

where the identity matrix, $\mathbf{I}$ is of dimension $(n_T \times n_T)$.

[6] The weights matrix appearing in Eqs. (12) and (13) is of different dimension than the weights matrix appearing in Eq. (3).

These marginal effects must be interpreted as the effect of a change in the amenities on the growth of the house prices. As before, the marginal effect can also be decomposed into three general components: (i) the direct effects (Eq. (6)); (ii) the total effects (Eq. (70)); and (iii) the indirect effects (Eq. (8)). As with the DID, the SDID approach is ineffective for retrieving the marginal mean contribution on price determination of the independent variables (or amenities) that do not vary over time. However, compared to the DID estimator, the main advantages of the SDID estimator are that: (i) it explicitly allows to test for the presence of a significant spatial spillover effect, through the parameter ρ, instead of relying on the unchecked assumption that such an effect is not significant; and (ii) it can be used to decompose the marginal effect into a wealthier process accounting for the spatial spillover effect through the coefficient ρ when it is significant.

The SDID approach can be seen as a generalization of the DID approach with an explicit way of testing for the absence of spatial autocorrelation related to the dependent variable. Such a test can be addressed with a standard t-test. If the parameter is significant, then inference based on the DID approach may be biased and the estimation of the marginal effects is also biased. However, as with the SAR specification of the HPM, the main challenge related to the SDID estimator lies in the development of a suitable weights matrix.

4. Building spatio-temporal weights matrices

One common point with spatial econometric specification (SAR–HPM and SDID) is that all the models rely on a given weights matrix. Thus, one challenge when dealing with cross-sectional data pooled over time is to make sure that the ρ coefficient measures the spatial spillover effect adequately. The spatial autoregressive specification needs to consider the spatial and the temporal dimensions of the data explicitly when building the weights matrices (Dubé and Legros, 2013a,b).

The general construction of such a weights matrix is in line with what some authors have already proposed to do: take into account the fact that some spatial databases are in fact a collection of spatial layers pooled over time (Smith and Wu, 2009; Huang et al., 2010; Dubé et al., 2011b; Dubé et al., 2013). Such an approach was recently used in an empirical investigation while not explicitly decomposing the effect according to time (Mathur and Ferrell, 2013). The construction of the spatial weights matrix in a spatio-temporal context is somewhat similar to the case of spatial panel data (Parent and LeSage, 2010) but differs in the sense that the number of observations may vary greatly among time periods and that observations are different in each time period.

The first step in building the weights matrix is to compile the data chronologically according to the time of the sales (date) and assign to assign a temporal value to each time period: the most remote time period receives the lowest value while the most recent one receives the highest value. This step allows a simple decomposition of the usual spatial weights matrix (Pace et al., 1998).

The second step consists of building the usual spatial relations, $w_{i_t j_r}$, among all the observations (Eq. (15)) based on the geographical distance $d_{i_t j_r}$ (Eq. (16)) separating an observation i collected in time period t and another observation j collected in time period r.

$$w_{i_t j_r} = \begin{cases} e^{-d_{i_t j_r}} & \forall\ t, r \\ 0 & \forall\ i = j \end{cases} \tag{15}$$

$$d_{i_t j_r} = \sqrt{(X_{i_t} - X_{j_r})^2 + (Y_{i_t} - Y_{j_r})^2} \tag{16}$$

where X_{i_t} represents the east–west geographical coordinates of the observation i collected in time period t, and Y_{i_t} represents the north–south geographical coordinates and so on for the (X_{j_r}, Y_{j_r}) coordinates.

This step gives a weights matrix expressing spatial relations regardless of the temporal relations for all the observations (Eq. (17)).

$$\mathbf{W} = \begin{pmatrix} 0 & w_{12} & \cdots & w_{1n_1} & \cdots & w_{1n_t} & \cdots & w_{1n_T} \\ w_{21} & 0 & \cdots & w_{2n_1} & \cdots & w_{2n_t} & \cdots & w_{2n_T} \\ \vdots & \vdots & \ddots & \vdots & \cdots & \vdots & \ddots & \vdots \\ w_{n_1 1} & w_{n_1 2} & \cdots & 0 & \cdots & w_{n_1 n_t} & \cdots & w_{n_1 n_T} \\ \vdots & \vdots & \cdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ w_{n_t 1} & w_{n_t 2} & \cdots & w_{(n_t n_1} & \cdots & 0 & \cdots & w_{n_t n_T} \\ \vdots & \vdots & \cdots & \vdots & \cdots & \vdots & \ddots & \vdots \\ w_{n_T 1} & w_{n_T 2} & \cdots & w_{(n_T n_1} & \cdots & w_{n_T n_t} & \cdots & 0 \end{pmatrix} \tag{17}$$

where the n subscript can be replaced by the N subscript if working with the SAR specification of the HPM instead of the SDID estimator. Thus, the weights matrix is of dimension $(n_T \times n_T)$ for the SDID approach, while being of dimension $(N_T \times N_T)$ for the HPM application.

Once the spatial relations have been formed and synthesized in the weights matrix (Eq. (17)), it is necessary to introduce temporal constraints on some elements since spatial representation alone does not account for the temporal causality: observation i_t cannot exert any influence on the observation j_r if $t > r$ since future realizations cannot influence past ones. Thus, it is necessary to introduce some constraints on the spatial weights matrix so as to obtain a spatio-temporal weights matrix that adequately expresses the possible relations among the observations i_t and j_r according to the time constraints.

To reflect the temporal constraints on the spatial relation, the third step consists in decomposing the general weights matrix to isolate the spatial multidirectional relation occurring in the same time period. This decomposition involves a block diagonal representation to make sure that the spatial relation holds between observations i_t and j_r only if $r = t$. This constraint provides a similar representation to those obtained in the panel specification, but where the spatial relations are not the same over time because the observations are different (Eq. (18)).[7] According to this notation, a general element of the block diagonal decomposition, $\mathbf{W}_{tt}$, is of dimension $(n_t \times n_t)$ when the SDID estimator is applied and of dimension $(N_t \times N_t)$ when the usual SAR–HPM is estimated, and captures the possible spatial relations among transactions occurring in the same time period.

$$\mathbf{W} = \begin{pmatrix} \mathbf{W}_{11} & 0 & 0 & \cdots & 0 \\ 0 & \mathbf{W}_{22} & 0 & \cdots & 0 \\ 0 & 0 & \mathbf{W}_{33} & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & \mathbf{W}_{TT} \end{pmatrix} \tag{18}$$

This representation of the spatio-temporal weights matrix ensures that the autoregressive coefficient, ρ, captures the multidirectional spatial spillover effect for observations collected in the same time period. This ensures that modelers take into account the particularity of the spatial data pooled over time. Moreover, since the spatio-temporal weights matrix introduces some constraints on the general elements, this procedure avoids potential problems related to the over-connection of the weights matrix (Smith, 2009).

Of course, there could be other ways to build such a spatio-temporal weights matrix. The more general specification accounts for the possible link between observations i_t and j_r if $t < r$, while the relation between i_t and j_r is impossible for $t > r$. That is, observation i collected in time period $t - p$ can be connected to the observation j collected in time period t, while the reverse is impossible. In such cases, the form of the spatio-temporal weights matrix takes into account the elements appearing in the lower triangular part (Eq. (19)).

$$\mathbf{W} = \begin{pmatrix} \mathbf{W}_{11} & 0 & 0 & \cdots & 0 \\ \kappa_1 \mathbf{W}_{21} & \mathbf{W}_{22} & 0 & \cdots & 0 \\ \kappa_2 \mathbf{W}_{31} & \kappa_1 \mathbf{W}_{32} & \mathbf{W}_{33} & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \kappa_{T-1} \mathbf{W}_{T1} & \kappa_{T-2} \mathbf{W}_{T2} & \kappa_{T-3} \mathbf{W}_{T3} & \cdots & \mathbf{W}_{TT} \end{pmatrix} \tag{19}$$

where the general matrix $\mathbf{W}_{t(t-p)}$ synthesizes the spatial connection between observation i collected in time period $t - p$ to the observation j collected in time period t and is of dimension $(n_t \times n_{t-p})$ in the SDID application and of dimension $(N_t \times N_{t-p})$ in the SAR HPM application. The scalar κ_p expresses the temporal distance between the two observations i and j and can be seen as a measure of actualization (Eq. (20)).

$$\kappa_p = \frac{1}{t - (t - p)} = \frac{1}{p} \tag{20}$$

The latter specification (Eq. (19)) takes into account the unidirectional spatial relation under the temporal constraints as well as the multidirectional spatial relation among observations in the same time period. What is less clear with this specification of the spatio-temporal weights matrix is how to isolate the source of the spatial effect (unidirectional of multidirectional). For this reason, it might be preferable to use the spatio-temporal weights matrix based on the block diagonal representation (Eq. (18)) if the strictly multidirectional spatial effect is to be isolated. It might also be possible to use the lower block triangular specification of the weights matrix in Eq. (19) to capture the spatially localized dynamic effect.[8]

As usual, the fourth and final step of the construction of the weights matrix, consists of a row-standardization of the matrix appearing in Eq. (18) or in Eq. (19). The spatio-temporal weights matrix adequately captures the spatial relations occurring in a given time period and eliminates the possible overestimation of the spatial spillover effect (LeSage and Pace, 2009; Dubé and Legros, 2013a).

[7] It should be noted that a particular observation is treated as being collected only once over time.

[8] In this case, the spatial weights matrix can be summarized by subtracting the **W** matrix in Eq. (18) from the **W** matrix in the Eq. (19). This new matrix, noted $\underline{\mathbf{W}}$ allows to isolate the effect of past observations on actual observations. This possibility is not explicitly considered here but can easily be incorporated to generate a simple extension of the model.

After these steps, the Eqs. (3) or (12) can be estimated using the maximum likelihood estimation method (LeSage, 1999) or any other methods, such as two stage least square (2SLS) or generalized method of moments (GMM), by imposing the constraint that the autoregressive coefficient, ρ must be less then one (in absolute value) to avoid the unit root problem.

5. An empirical example

To illustrate the potential of the SDID approach, the results based on the ordinary least square (OLS) obtained from Eq. (9) and on the maximum likelihood (ML) approach for Eq. (12) are compared. The experiment is based on the implementation of a commuter rail transit (CRT) system in the northern suburbs of the city of Montreal, Canada.

5.1. Changes in mass transit services

The North Shore CRT service was deployed progressively, between May 1997 and January 2007, from downtown Montreal (on the island) towards the north of the metropolitan area. The first two stations (Blainville and Sainte-Thérèse) were inaugurated on May 1, 1997, while another station (Rosemére) opened on January 1, 1998. (Map 1). Almost ten years after the first stations opened on the north shore, the line was extended to Saint-Jérôme in January 2007, which is still the farthest service point on this route. In fact, the north line of the CRT was brought into service in 1997 because a bridge on Route 117 linking the north shore with the Island of Montreal was under renovation. The success of the line was such that the Montreal Metropolitan Transportation Agency (MTA) decided to make the service permanent and increase the number of departures.

First, actual estimated car travel time (in minutes) to the nearest station is indicated for each location based on the 2009 situation (Fig. 1). Secondly, car travel time improvement is measured for each repeat sale pair considering both its location in time (before or after opening of train stations) and space. As can be seen, previously operating stations or train lines apparently impede improvement at the local scale, as is the case around the Deux-Montagnes train station which has been operating since the early 20th century.

A major feature of the CRT service is that it operates using an older single-lane railway track. The literature reports on the potential issue of measuring the change in accessibility when the infrastructure needs to be constructed and when the market anticipates the actual effect of this new potential before it is effective (McDonald and Osuji, 1995; Knaap et al., 2001; McMillen and McDonald, 2004; Yiu and Wong, 2005; Immergluck, 2009). Considering that, in this case, the delay between the announcement and the implementation of the service is pretty short, the anticipation effect is assumed to be negligible and, consequently, actual dates of station opening are considered for measuring change in access to the CRT service.

The total number of passengers using the North Shore CRT service significantly increased between 1997 and 2009 (Table 1); it more than doubled in about ten years. The total number of departures towards Montreal has more than doubled between 1997 and 2001 (from 6 to 13), although it has since been reduced, falling to 11 in 2002, and then to 10 in 2007. It is important to note that only four departures out of ten have downtown Montreal as their destination, with the north line currently benefitting from four connections with the Montreal subway network (the de la Concorde, Parc, Vendome, and Lucien-L'Allier stations). Each train station provides parking lots enabling park-and-ride to favor multimodal moves towards the city. The six bridges connecting the Island of Laval to the north shore of Montreal and the seven bridges connecting the Island of Laval to the Island of Montreal are generally highly congested during morning and afternoon peak periods, which is an incentive for car drivers to use PMT. Only one bridge (Charles-de-Gaulle) directly connects the north shore of Montreal to the Island. Parking lots have been gradually enlarged to cope with increasing demand (Table 2) since most passengers using the CRT service access the stations by car (as drivers and passengers), except for the station of Sainte-Thérèse.

5.2. House transaction data

The data on single-family house transactions, property characteristics, and prices come from the Greater Montreal Real Estate Board (GMREB) and have been reviewed and structured by the Altus Group (Quebec City, Canada), an international appraisal firm operating throughout Canada. From the second quarter of 1992 to the final quarter of 2009, 93,239 transactions were recorded. However, house sales are only considered in the estimation process if: i. the house sale (and resale) price is available; ii. the sale (and resale) date is available; iii. the sale (and resale) price is more than $50,000 (CAD dollars). As previously mentioned, the logarithmic transformation of the dependent variable is proven to be closer to the normal distribution than the original variable (Fig. 2).

Considering the constraints related to the inclusion in the database and considering the fact that the DID and SDID estimators introduce an additional constraint on the construction of the database, the final sample is composed of 27,311 pairs[9] of transactions (Table 3).

It is interesting to observe the behavior of the dependent variable of the SDID approach, the logarithmic transformation of the resale-to-sale price ratio. The comparison of mean values suggests that the mean price rise between sale and resale is

[9] It should be noted that the total number of repeated transactions is about 30% of the total sample sales. This proportion is quite high compared to other repeated sales approaches (Clapp et al., 1991; Abraham and Schauman, 1991; Case and Shiller, 1989) and similar to the study of Dubé et al. (2011a).

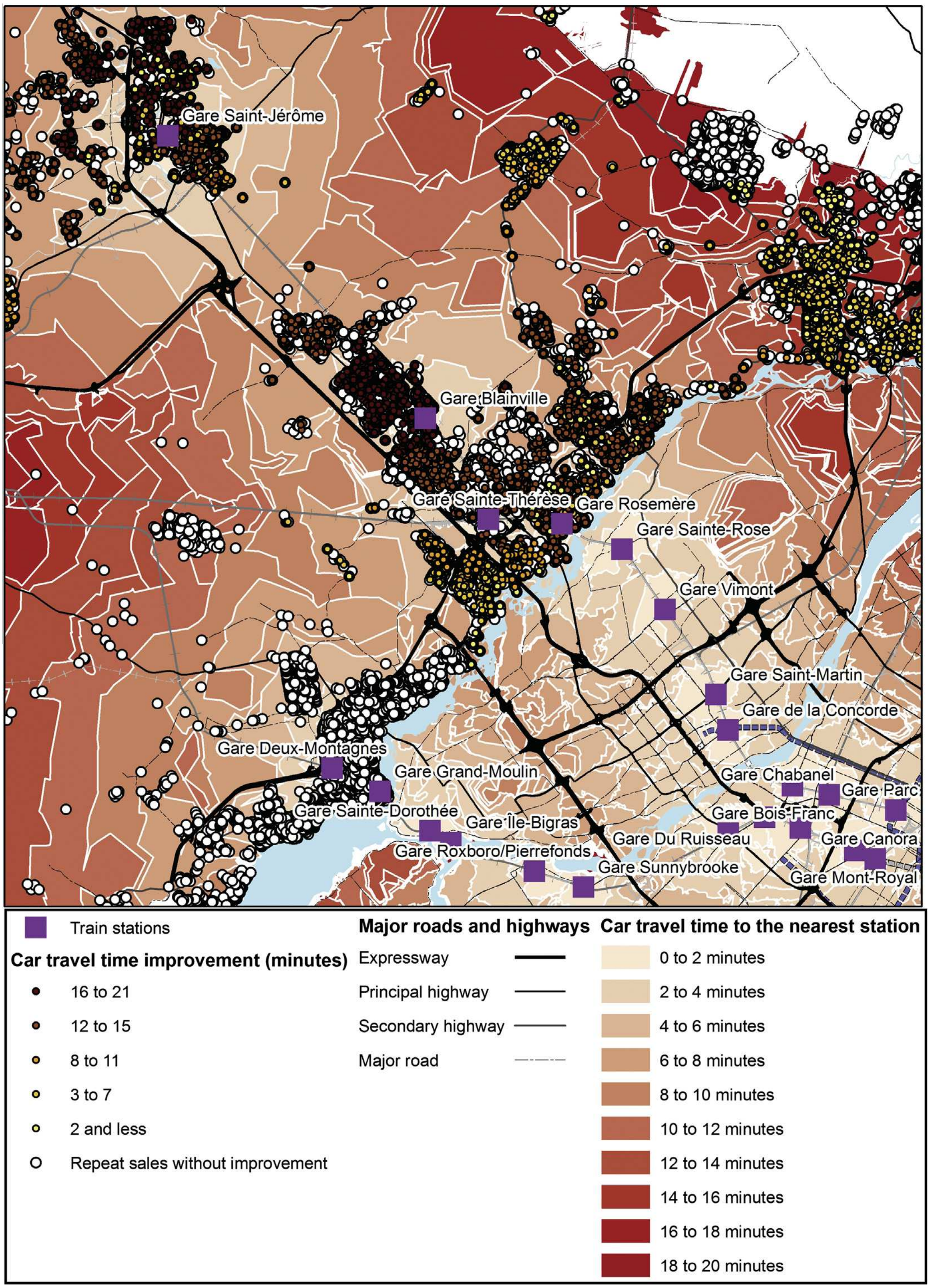

Fig. 1. Commuter Rail Train.

about 31%, varying between −84% and +187%. The distribution of the variable is slightly skewed to the left hand side, although it is not too far from a normal distribution, while the kurtosis is statistically equivalent to that of the latter. The kurtosis is statistically equal to the one of the normal distribution (Fig. 3).

Table 1
Change over time in the use of the CRT service, 1998–2008.

CRT station	Passengers per day		
	1998	2003	2008
Saint-Jérôme	n.a.	n.a.	633
Blainville	554	936	1460
Sainte-Thérèse	1267	2035	2906
Rosemère	1744	2999	3920

Legend: n.a.: not available.

Table 2
Increases over time in the number of parking lots for each CRT station, 1998–2008.

CRT station	Parking		
	1998	2003	2008
Saint-Jérôme	n.a.	n.a.	378
Blainville	475	582	582
Sainte-Thérèse	600	664	664
Rosemère	128	352	401

Legend: n.a.: not available.

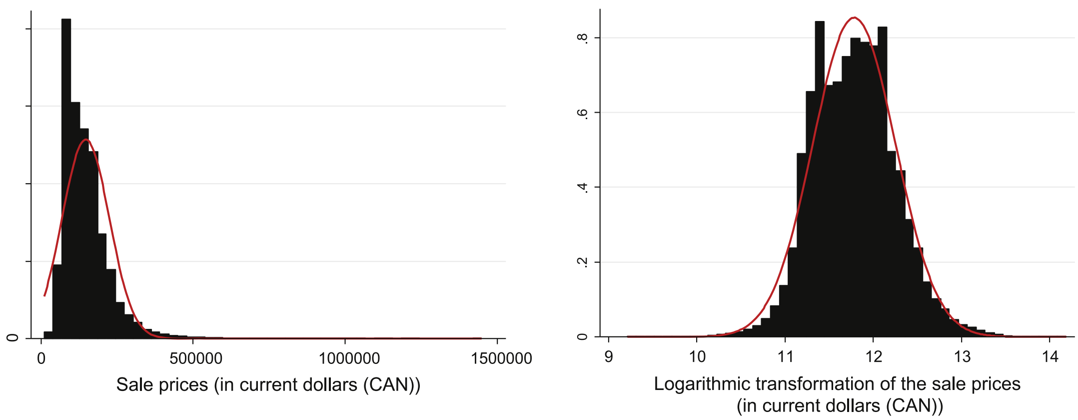

Figure 1.1
Sale price

Figure 1.2
Logarithm transformation of sale price

Fig. 2. Distribution of sales prices.

Table 3
Total number of pairs of house transactions given the total number of transactions.

Transactions	Number	Mean sale price (CAD dollars)	Mean resale price (CAD dollars)
All	27,311	$120,933	$164,480
2	20,800	$116,945	$161,181
3	5271	$130,788	$173,750
4	1076	$144,038	$179,556
5	145	$158,698	$186,374
6	16	$158,000	$184,531
7 or more	3	$147,333	$173,833

With regard to changes in the environmental amenities related to changes in mass transit systems supply, few houses experience a change in pedestrian accessibility to a CRT station (Table 4). In fact, only 395 houses gain access to the new CRT service between the time of the first sale and the second sale (resale). These houses also improve their car accessibility to CRT stations (in minutes). The analysis of the change in commuting time to the nearest station suggests that houses with better pedestrian access to a station also gain considerable travel time by car. Houses within 0 to 1500 m of the nearest sta-

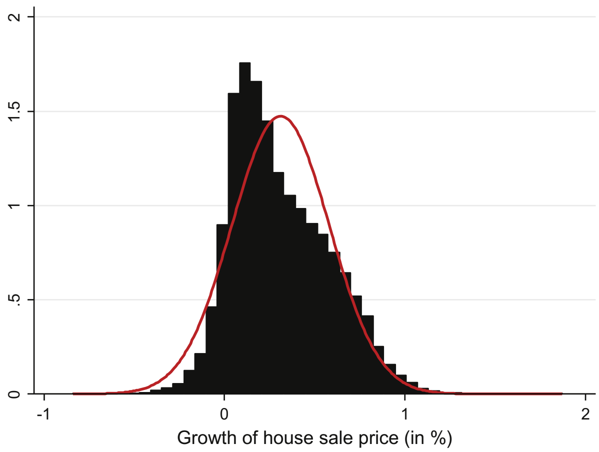

Fig. 3. Distribution of growth of sales prices.

Table 4
Number of transactions experiencing changes in environmental amenities.

Environmental amenities	Mean	Min.	Max.	N
Within 0 to 500 m walking distance	0.0011	0	1	31
Within 500 to 1000 m walking distance	0.0040	0	1	109
Within 1000 to 1500 m walking distance	0.0093	0	1	255
Automobile distance (in minutes)	-10.4765	−21	−1	4019

Min.: minimum, Max.: maximum., N: number.

tion see their car accessibility improved by almost 15 min. Finally, it is interesting to note that those houses that have better pedestrian accessibility to CRT stations are not necessarily those that benefit from a better car accessibility (Table 5).

5.3. Estimation approach

The form of the SDID estimator (Eq. (12)) requires the weights matrix, $\mathbf{W}$, to be of full rank. This is necessary to ensure that the inverse of the expression $(\mathbf{I} - -\mathbf{W}\rho)$ exists. This constraint comes from the reduced form of the SDID estimator (Eq. (12)), expressing the data generating process (DGP) of the model (Eq. (21)).

$$\Delta\mathbf{y}_{irs} = (\mathbf{I} - \mathbf{W}\rho)^{-1}(\Delta\mathbf{D}_{irs}\delta + \Delta\mathbf{X}_{irs}\beta + \Delta\mathbf{Z}_{irs}\theta + \Delta\epsilon_{irs}) \tag{21}$$

Given the form of the dependent variable $\Delta\mathbf{y}_{irs}$, it is rare that repeated-sales occur in the first time periods (Table 6), while they become more frequent following some periods (Table 7). Thus, to make sure that the weights matrix is of full rank, it is necessary to eliminate some observations in the beginning of the sample. This solution is similar to the Cochrane–Orcutt transformation applied to time-series analysis, except that applying the weights matrix requires that several observations be excluded.

Table 5
Number of transactions experiencing changes in car time travel to nearest CRT station.

Time gain range	Mean	Number
All	−10.4765	4019
0–2 min	−1.5646	356
2–4 min	−3.6018	304
4–6 min	−5.5809	556
6–8 min	−7.4145	427
8–10 min	−9.5758	198
10–12 min	−11.6625	240
12–14 min	−13.5574	827
14–16 min	−15.4096	581
16–18 min	−17.3289	453
18–20 min	−19.0933	75
More than 20 min	−21.0000	2

Table 6
Total number of transactions in the first quarters.

Date (quarter)	Number of sales	Number of resales
1992 Q2	199	0
1992 Q3	227	1
1992 Q4	280	0
1993 Q1	490	4
1993 Q2	332	2
1993 Q3	218	4
1993 Q4	272	6
Total	2018	17

Table 7
Total number of transactions after some quarters.

Date (quarter)	Number of sales	Number of resales
1994 Q1	651	27
1994 Q2	450	18
1994 Q3	190	12
1994 Q4	262	24
1995 Q1	494	47
1995 Q2	313	36
1995 Q3	216	35
1995 Q4	347	37
Total	2927	236

Thus, by eliminating the observations for the years 1992 and 1993, we are left with 27,294 pairs of transactions for estimating the model.[10] The usual procedure of the maximum likelihood (ML) estimation may be applied with the row-standardized weights matrix. Since all time periods contain a sufficient number of observations, the weights matrix is of full rank and the model DID (Eq. (9)) and SDID (Eq. (12)) can be estimated and the results can be compared.

5.4. Comparing DID and SDID results

For the exercise, the weights matrix **W** isolates the spatial multidirectional effect occurring in the growth of sale prices (Eq. (18)). Thus, if the second sale (resale) appears in the same time period (quarter), then the observations are spatially connected through the inverse exponential distance transformation. In other words, the choice of the weights matrix implies that the model assumes that house price growth is influenced by the rise in prices of other houses in the vicinity in the same time period.

The findings show that proximity to a commuter rail station has a significant impact on house price growth, and thus, on house prices. The models (Eqs. (9) and (12)) incorporate all the possible characteristics that vary over time and that may affect the house price determination process. Since it is assumed that house characteristics are stable over time if no other information is available, few independent variables related to the variation in the amenities, $\Delta\mathbf{X}_{irs}$, are included in the final specifications.

The coefficients are quite comparable between both approaches. For both estimations, the coefficients related to a walking distance of less than 1500 m vary between 0.02 and 0.05. Using the DID estimator, the marginal effect related to this proximity commands a higher growth of house prices varying from 2.2% points (500–1000 m), to 3.5% points (1000–1500 m) and 4.8% points (0–500 m), while each minute of gain in car time distance to the nearest train station results in a higher growth of house prices of 0.06% (Table 8).

Findings obtained with the SDID estimator suggest that the total marginal effect related to station proximity translates into a premium on growth of house prices that varies from 2.3% points (500–1000 m), to 3.8% points (1000–1500 m) and 5.2% points (0–500 m), while each minute of gain in car time distance to the nearest train station results in an increase of the growth of house prices of more than 0.06% (Table 9). In both cases, the total effect related to total gain in driving time may result in a premium as high as an increase in growth of house prices of 1.3% points for houses experiencing the highest variation (22 min).

In the SDID specification, the determination of the mean marginal effect lies in the computation of various marginal spatial effects. The direct and the total marginal effects rely on the form of the weights matrix **W** and the amplitude of the spatial autoregressive coefficient, ρ (Eqs. (6) and (7)). Thus, it is possible to investigate the variation in the marginal effects according to the extreme values taken by calculating the total marginal effects (Table 10). The decomposition of the total

[10] The data base contains 27,311 observations and there are 17 observations recorded in the first two years.

Table 8
Estimation results.

Variables	DID Eq. (9)		SDID Eq. (12)	
	β	t-stat	β	t-stat
1994 – First quarter	Ref.	Ref.	Ref.	Ref.
1994 – Second quarter	−0.0101	−1.53	−0.0101	−1.54
1994 – Third quarter	−0.0014	−0.13	−0.0017	−0.18
1994 – Fourth quarter	−0.0295	−3.75	−0.0296	−3.78
1995 – First quarter	−0.0250	−4.22	−0.0251	−4.248
1995 – Second quarter	−0.0215	−2.99	−0.0216	−3.02
1995 – Third quarter	−0.0512	−6.16	−0.0506	−6.10
1995 – Fourth quarter	−0.0440	−6.40	−0.0437	−6.38
1996 – First quarter	−0.0432	−8.50	−0.0428	−8.46
1996 – Second quarter	−0.0328	−5.25	−0.0326	−5.24
1996 – Third quarter	−0.0517	−6.72	−0.0514	−6.70
1996 – Fourth quarter	−0.0403	−7.14	−0.0399	−7.01
1997 – First quarter	−0.0279	−5.76	−0.0274	−5.69
1997 – Second quarter	−0.0430	−7.41	−0.0426	−7.35
1997 – Third quarter	−0.0533	−6.85	−0.0521	−6.73
1997 – Fourth quarter	−0.0436	−6.88	−0.0430	−6.80
1998 – First quarter	−0.0433	−8.53	−0.0430	−8.48
1998 – Second quarter	−0.0395	−7.20	−0.0388	−7.11
1998 – Third quarter	−0.0553	−8.34	−0.0541	−8.19
1998 – Fourth quarter	−0.0367	−5.95	−0.0365	−5.93
1999 – First quarter	−0.0195	−4.16	−0.0197	−4.22
1999 – Second quarter	−0.0145	−2.78	−0.0148	−2.85
1999 – Third quarter	−0.0117	−1.85	−0.0114	−1.82
1999 – Fourth quarter	−0.0017	−0.29	−0.0018	−0.32
2000 – First quarter	0.0200	4.39	0.0190	4.20
2000 – Second quarter	0.0324	6.07	0.0310	5.84
2000 – Third quarter	0.0311	5.09	0.0298	4.89
2000 – Fourth quarter	0.0431	8.17	0.0411	7.83
2001 – First quarter	0.0616	14.37	0.0590	13.89
2001 – Second quarter	0.0708	14.89	0.0684	14.429
2001 – Third quarter	0.0814	14.79	0.0787	14.359
2001 – Fourth quarter	0.1053	21.75	0.1017	21.089
2002 – First quarter	0.1489	37.28	0.1439	36.19
2002 – Second quarter	0.1838	38.87	0.1786	37.93
2002 – Third quarter	0.2159	41.61	0.2096	40.58
2002 – Fourth quarter	0.2546	53.28	0.2462	51.76
2003 – First quarter	0.3099	74.14	0.3002	72.35
2003 – Second quarter	0.3292	68.67	0.3192	67.03
2003 – Third quarter	0.3637	73.64	0.3519	71.80
2003 – Fourth quarter	0.3982	83.55	0.3855	81.59
2004 – First quarter	0.4452	106.27	0.4308	104.15
2004 – Second quarter	0.4689	103.98	0.4544	101.925
2004 – Third quarter	0.4937	99.91	0.4777	97.795
2004 – Fourth quarter	0.5093	105.21	0.4921	103.015
2005 – First quarter	0.5495	130.45	0.5306	128.425
2005 – Second quarter	0.5562	121.93	0.5372	119.80
2005 – Third quarter	0.5742	114.79	0.5542	112.58
2005 – Fourth quarter	0.5868	114.71	0.5659	112.47
2006 - First Quarter	0.6115	139.91	0.5894	138.11
2006 – Second quarter	0.6190	133.63	0.5968	131.66
2006 – Third quarter	0.6355	116.43	0.6123	114.19
2006 – Fourth quarter	0.6421	121.97	0.6178	119.77
2007 – First quarter	0.6705	153.83	0.6439	152.77
2007 – Second quarter	0.6776	144.243	0.6510	142.70
2007 – Third quarter	0.6943	127.19	0.6664	125.09
2007 – Fourth quarter	0.71459	130.97	0.6853	128.99
2008 – First quarter	0.7340	156.78	0.7029	156.18
2008 – Second quarter	0.7539	150.37	0.7223	149.32
2008 – Third quarter	0.7601	135.98	0.7280	134.221
2008 – Fourth quarter	0.7585	116.02	0.7274	113.68
2009 – First quarter	0.7645	151.57	0.7315	150.70
2009 – Second quarter	0.7719	156.58	0.7385	156.08
2009 – Third quarter	0.7830	137.72	0.7494	136.05
2009 – Fourth quarter	0.8024	145.98	0.7679	144.76
Foreclosure	−0.1163	−36.33	−0.1167	−36.55
Risk	−0.0755	−25.91	−0.0755	−26.00
Succession	−0.0784	−7.00	−0.0745	−6.67

Table 8 (*continued*)

Variables	DID Eq. (9)		SDID Eq. (12)	
	β	*t*-stat	β	*t*-stat
Transfer	−0.0185	−4.46	−0.0195	−4.72
Car time distance	−0.0006	−2.89	−0.0006	−2.70
Walking distances				
0–500 m	0.0482	2.10	0.0490	2.13
500–1000 m	0.0224	1.80	0.0225	1.81
1000–1500 m	0.0354	4.21	0.0362	4.33
ρ	n.a.	n.a.	0.0500	25.16
N	27,294		27,294	
R^2	0.7810		0.7818	
$\overline{R}^2$	0.7804		0.7813	

Table 9
The (mean) marginal effect of a change in MT supply on growth of house prices.

Model specification (equation number) Environmental amenities	DID (9) Marginal effect	SDID Eq. (12) Marginal effect		
		Direct	Indirect	Total
Walking distance 0–500 m	0.04825	0.04955	0.00261	0.05215
Walking distance 500–1000 m	0.02244	0.02230	0.00118	0.02347
Walking distance 1000–1500 m	0.03538	0.03607	0.00190	0.03797
Car time distance (in minutes)	−0.00064	−0.00059	−0.00003	−0.00062

marginal effect suggests, in line with the literature, that some houses adjacent to the commuter rail station may experience a lower growth of house price due to the presence of negative externalities, whereas those located further away will benefit from a higher growth of house prices, with the latter lessening thereafter. This is noted through the negative value on the lower 1% individual total marginal effect. As a consequence, the form of the location rent is not necessarily linear, but instead taken an inverse "U" shape. In other words, even if the mean effect is positive and significant, some houses may experience lower growth of house price and thus lower properties values as compared to the houses experiencing no changes in environmental amenities.

As with houses within walking distance from the train stations, a change in car driving time to the closest commuter train station results in a higher growth of house prices varying between 0.12% points and 0.003% points for each minute gained (Table 10). The variation never turns out to be negative, even at the lower 1% points centile. In the end, the impact for the houses experiencing the more pronounced gains in car travel time varies between a premium on house price growth of 2.68% points and 0.07% points.

5.5. Discussion

Even if the total marginal effects of the DID estimator are quite comparable to the direct marginal effects of the SDID estimator in the current case, the inclusion of the indirect marginal effects brings in some additional information about the calculation of the total marginal effects in the SDID case. Thus, the real comparison that must be made is the comparison of the total marginal effects with both estimators.

The important difference between the DID and SDID estimators lies in the significance of the ρ coefficients since it affects the calculation of the total and indirect marginal effects. As can be seen, the comparison is largely dependent upon the magnitude of the ρ coefficient of the SDID estimator. In the current case, the ρ coefficient, even if weak in magnitude, is highly significant, suggesting that using the DID estimator can introduce some bias on the estimated coefficients, as well as in the

Table 10
Variation of the total marginal effect of a change in MT supply on growth of house prices.

Environmental amenities	Total	Lower 1%	Higher 99%
Walking distance 0–500 m	0.05215	−0.01409	0.10707
Walking distance 500–1000 m	0.02347	−0.01042	0.05643
Walking distance 1000–1500 m	0.03797	0.01419	0.05968
Car time distance	−0.00062	−0.00122	−0.00003

calculation of the marginal effects. Both total marginal effects will be identical if and only if the autoregressive coefficient, ρ, is not significant (Eq. (21)).

Even if the total marginal effects as obtained with the SDID are only about 0.1% points to 0.3% points higher than those obtained using the DID estimator, it must be stressed that this simple difference may result in large differences once transposed in values ($CAD) and when the effect is applied to the total stock values (Dubé et al., 2013, 2011a). This is even more important considering that the premium effect is measured on the house price growth. For example, assuming that the normal price growth is 3% per year, a house of $CAN 100,000 will worth $CAN 134,391 in 10 years, while its value will be $CAN 138,357 if the growth rate is 3.3%. This represents, for a single house, a premium of $CAN 3,966. Thus, even if the indirect marginal effect is low in the present case, since the value of the spatial autoregressive coefficient ρ is low, it can represent a large amount over many time periods.

In the end, the superiority of the SDID estimator is directly related to the magnitude of the autoregressive coefficient, ρ. If ρ is high, then the calculation of the total marginal effect is biased when using the DID estimator. The significance of the ρ parameter indicates that even if the DID estimator allows to control for the latent spatial structure hidden in the error term of the standard hedonic price equation, it does not capture all the effects of the spatially structured data. The general formulation of the SDID estimator may allow other researchers to use this general framework to evaluate the effect of exogenous environmental changes on real estate values.

6. Conclusion

This paper presents a spatial Difference-in-Differences (SDID) estimator that accounts for both the spatial location of individual properties and the temporal dimension of the database. The SDID estimator captures the effects of exogenous changes in environmental amenities, such as the introduction of a new commuter rail service, on property values where some houses experience a change in accessibility while others do not. The final form of the estimator isolates such an impact while accounting for possible spatial spillover effects, referred to by Small and Steimetz (2012) as being strictly technological, since nominal price evolution is captured through a series of temporal dummies.

An important feature of this paper is to show that such an estimator may generate different estimations of the value impact of a change in public transport policy and allows for a wealthier interpretation of the marginal effect. The calculation of the marginal effect using the spatial autoregressive specification of the hedonic price equation differs from that obtained with the usual ordinary least squares approach since it relies on a spatial multiplier. While the DID approach actually controls for many constant effects, including the latent spatial component that may, otherwise, generate spatial autocorrelation among residuals (Dubé et al., 2011a), the SDID provides a more consistent estimator that accounts for possible spillover effects, a major methodological gain as compared to the DID version. The SDID estimator also allows for the decomposition of the total marginal effect of a change in the environmental amenities into direct, total, and indirect components. The benefit of using the SDID estimator instead of the DID estimator depends on the magnitude of the spatial autoregressive coefficient ρ. The SDID estimator is of particular importance where the spatial autoregressive coefficient, ρ, is assigned a significant and high value.

The estimation results for the commuter rail transit (CRT) service linking downtown Montreal to the North Shore area suggest there is little gain from using the SDID estimator instead of the DID estimator. However, this may be because this line was implemented in an area where many alternative (substitutes) transportation modes exist (Liu et al., 2009) or because there is a lack of integration between a pure transport supply (TS) and a pure demand management (DM) (Ma and Lo, 2012). In our opinion, it in no way lessens the importance of developing the SDID estimator: resorting to the latter might be a convenient way to test for the presence/absence of spatial autocorrelation related to the dependent variable using a simple t-test instead of assuming that this effect is not significant.

In this paper, the SDID estimator is based only on the spatial multidirectional spillover effect and omits a possible dynamic spatial effect, related to the fact that past growth may influence current growth. Such an approach, which consists in decomposing the spatial effect into its current spatial effect and past (dynamic) spatial effect, may well be implemented in the SDID estimator (see Dubé and Legros, 2013b). That said, the estimator developed in this paper has the clear advantage over the classical difference-in-differences (DID) estimator of accounting for the spatial dimension that would otherwise be omitted.

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