Spatial Econometrics and Spatial Data Pooled over Time: Towards an Adapted Modelling Approach

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Abstract: *This paper addresses the possible problem related to using strictly spatial modelling techniques for spatial data pooled over time. For these data, such as real estate, the spatial dimension is present, but subject to constraints related to temporal dimension. Three empirical examples are presented to investigate the impact of neglecting the temporal dimension in spatial analysis and to show how such an approach overestimates the pattern of spatial dependence, and overestimates the spatial autoregressive coefficient estimated. If generalized to all other empirical applications, this conclusion may have important considerations if one tries to measure the effect of extrinsic amenities on house prices.*

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Introduction

Although spatial econometrics has been in development for some forty years[1] (Goodchild, 2009; Haining, 2009), advances in spatio-temporal modelling are relatively recent (Elhorst, 2003; Baltagi and Li, 2004; Baltagi et al., 2003, 2007; Kapoor et al., 2007; Yu and Lee, 2008; Lee and Yu, 2010; Parent and Lesage, 2011). Advances in spatio-temporal issues deal primarily with models applied to panel-type data. However, spatio-temporal data do not systematically adopt a panel form, cylindrical or not. In many cases, the spatial data are gathered in time without the units being observed more than once on the temporal horizon. The case for real estate transaction data is particularly striking: data include actual spatial characteristics and are collected over time without the majority of observations being repeated (Case and Shiller, 1989; Abraham and Schauman, 1991; Clapp *et al.*, 1991; Dubé *et al.*, 2011a).

Traditionally, when individual spatial data pooled over time are used, it is assumed that the effect of time is negligible in the data-generating process, which justifies the use of current spatial analysis methods. Some of the recent studies have shed light on the importance of considering temporal dimension in spatial studies (LeSage and Pace, 2009; Dubé and Legros, 2013a). Other studies have suggested taking into consideration the peculiarity of spatial data pooled over time by designing a spatio-temporal weights matrix to consider both dimensions simultaneously (Smith and Wu, 2009; Huang et al., 2010; Nappi-Choulet and Maury, 2011; Dubé and Legros, 2011; Dubé *et al*., 2011b). The unique form of the matrix allows us to retain the properties of existing spatial statistics and spatial models.

The construction of a unique spatio-temporal weights matrix is based on two distinct elements: a temporal weights matrix and a spatial weights matrix. The temporal weights matrix considers the unidirectionality of relations: past observations can have an influence on current observations, while the inverse is quite improbable,[2] even impossible (according to the time step chosen). This matrix allows us to identify the observations that are recorded during the same period, in addition to the observations that precede or follow. The spatial weights matrix considers the multidirectionality of relations: an observation influences the behaviour of neighbours, while the neighbours also influence one's own behaviour. A spatio-temporal weights matrix combines spatial multidirectional relations for a same period in addition to pinpointing unidirectional relations linking past spatial observations with present and future spatial observations.

The objective of this paper is to show how the development of spatio-temporal weights matrices and their use in spatial econometric approaches[3] can be used to test for temporal reality in the compilation of individual and non-recurring spatial data. More specifically, the paper attempts to verify whether the conclusions as to a possible overestimation of the spatial effect in a spatio-temporal context are verified empirically and how this overestimation can reflect on the magnitude of estimated autoregressive coefficients. The paper also shows how the construction of spatio-temporal weights matrices can help in developing new variables that can then be introduced in the model in order to monitor spatialized temporal dynamic effects. Three empirical examples are presented using real estate transaction data from Québec, Canada (1990-1996), Paris, France (1990-2001) and Lucas County, USA (1993-1998).

The paper is divided into four sections. The first section introduces the process for structuring spatial data pooled over time. It shows how the temporal dimension (unidirectional) can play an important role in determining spatial relations (multidirectional) and shows the importance of restructuring relations in hybrid form. The second section explains how to consider the two types of relations – spatial multidirectional and temporal unidirectional – using a spatio-temporal weights matrix that considers both the spatial and temporal characterization of the observations. The third section presents several empirical applications conducted on real estate transactions in Canada, France and the United States to draw general conclusions on the influence that the development of a spatio-temporal matrix can have on the possible bias relating to only considering the spatial dimension when data is pooled over time. A brief conclusion follows, summarizing the main findings.

Structuring spatial data pooled over time

Representing "spatial interaction effect" among observations stems from the first law of geography (Tobler, 1970), which stipulates that all phenomena are interrelated, but that those closest are more strongly interrelated. This view is based on a two-dimensional structure (latitude (Y), longitude (X)) allowing the establishment of the distance separating two observations (Figure 1).

INSERT FIGURE 1 HERE

The configuration of some spatial databases means that this two-dimensional representation neglects the temporal aspect of individual spatial observation collection (Figure 2). In fact, the structuring of data is related more to a collection of spatial layers (one per period) pooled over time. Thus, the "spatial distance" metric separating the observations hides a basic reality: space is not the only dimension in the data collection process. To spatial distance one must necessarily add the temporal distance, keeping in mind the unidirectional effect of this dimension.

INSERT FIGURE 2 HERE

In spite of this particularity, most empirical applications using this type of data continue to implicitly assume that the time dimension has no impact, given that analyses are based on classical spatial methods, in spite of the fact that this rather strong hypothesis (LeSage and Pace, 2009; Dubé *et al.*, 2011b; Dubé and Legros, 2013b) is rarely verified and validated. An initial attempt at formalizing the spatial and temporal links among observations and including the temporal reality of spatial data pooled over time dates back more than ten years (Pace *et al.*, 1998, 2000). Since then, some applications have reintroduced this framework of analysis for given special empirical applications (Tu *et al.*, 2004; Sun *et al.*, 2005) or to serve as a starting point for spatio-temporal modelling (Nappi-Choulet and Maury, 2009). However, this approach has the disadvantage of not cross-referencing spatial and temporal data, but rather using spatial and temporal weights matrices independently. In fact, the matrix product of the two weights matrices only indirectly captures spatio-temporal effects (Smith and Wu, 2009).

Another way of incorporating the "temporal distance" matrix in spatio-temporal modelling is to specify a temporal autoregressive process of the error term (Gelfland *et al.*, 1998). This specification was adopted again to control for the dynamic effect of the determination of real estate values while considering the effects of spatial spillovers (Smith and Wu, 2009). While this process has the advantage of considering the unidirectionality of the temporal effect, it nevertheless neglects the geographical location of the observations and thus supposes that the dynamic effect is identical for observations that are spatially separated, but temporally close (Dubé and Legros, 2011).

Only a specification that allows for the simultaneous control of spatial and temporal distance can make allowances for the true process of structuring individual spatial observations collected over time (Dubé *et al.*, 2011b). Such a structure must thus consider both spatial and temporal distances (Figure 3).

INSERT FIGURE 3 HERE

One interesting solution is the development of a spatio-temporal weights matrix that considers spatial and temporal realities simultaneously. This approach allows for the control of the spatial multidirectional feedback effect for a given time period. In addition, the creation of a group of weights matrices also permits the development of new explanatory variables that can be added to models in order to monitor various spatio-temporal relationship patterns.

Construction of a spatio-temporal weights matrix

The construction of a spatio-temporal weights matrix is based on the development of two matrices: a spatial weights matrix and a temporal weights matrix. Each of these matrices has their own properties (Dubé *et al.*, 2011b, 2013b) that give them a different structure. Nevertheless, they normally allow for the interconnection of N_T observations[4] between them.

Spatial weights matrix

A spatial weights matrix, with the dimension $N_T \times N_T$, allows the establishment of spatial relations between two observations, *i* and *j*, based on a general element, s_{ij}. The general element is normally defined in accordance with the inverse distance separating the observations *i* and *j*, d_{ij}, while introducing a friction parameter, α, penalizing to a greater or lesser degree for distances[5] (Equation 1).

$$s_{ij} = \begin{cases} d_{ij}^{-\alpha} & \text{if } d_{ij} \leq \bar{d} \quad \forall i \neq j \\ 1 & \text{if } d_{ij} = 0 \quad \forall i \neq j \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

where $\bar{d}$ represents a threshold distance beyond which spatial influence between two observations is supposed null. In the end, all of the individual elements permitting the spatial linking of observations between them are used to generate the non-row-standardized spatial weights matrix, **S** (Equation 2).

$$\mathbf{S} = \begin{bmatrix} 0 & s_{12} & \cdots & s_{1j} & \cdots & s_{1N_T} \\ s_{21} & 0 & \cdots & s_{2j} & \cdots & s_{2N_T} \\ \vdots & \vdots & \ddots & \vdots & \cdots & \vdots \\ s_{i1} & s_{i2} & \cdots & s_{ij} & \cdots & s_{iN_T} \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ s_{N_T1} & s_{N_T2} & \cdots & s_{N_Tj} & \cdots & 0 \end{bmatrix} \quad (2)$$

The construction of the matrix is normally, but not exclusively, exogenous (Chasco and Lopez, 2008; Fingleton, 2009). Notwithstanding the debates surrounding the manner of designing the weights matrix (Giacomini and Granger, 2004; Bhattacharjee and Holly, 2011), one of the challenges is to set the optimal threshold distance parameter, $\bar{d}$. Some have suggested adopting values that, to the best of their knowledge, reflect the reality analyzed by the modeller (Getis, 2009). Others suggest adopting a value that maximizes the spatial autocorrelation estimate (Boots and Dufournaud, 1994). In any case, determining the optimal structure of the matrice's elements remains a challenge (Getis and Aldstadt, 2004).

Once the spatial weights matrix is constructed, it is common practice to row-standardize it. Row-standardization ensures that the results obtained can be comparable among themselves, and makes interpreting the spatially-lagged variables easier. Row-standardization includes taking each of the elements of a line and dividing them by the sum of the line's elements (Equation 3).

$$s_{ij}^{*} = {s_{ij}}\Big/{\sum_j s_{ij}} \quad (3)$$

The row-standardized weights matrix, **S***, is then used to calculate statistics that detect the presence of spatial autocorrelation or to estimate an autoregressive parameter.

Temporal weights matrix

A temporal weights matrix, of dimension $N_T \times N_T$, also permits the establishment of temporal ties between two observations, *i* and *j*, based on a general element, t_{ij}. A general element is defined according to the time distance separating the observation *i*, whose temporal value is noted by v_i, and observation *j*, whose temporal value is noted v_j. The inverse of the temporal distance separating observations *i* and *j*, $v_i - v_j$, is thus considered, while introducing a friction parameter, γ, allowing for the more or less strong weighting of time distances[6] (Equation 4).

$$t_{ij} = \begin{cases} \kappa\left(v_i - v_j\right)^{-\gamma} \text{if } v_i - v_j \leq \bar{v}_p;\ \forall i \neq j; v_i \neq v_j \text{and } v_i > v_j \\ \kappa\left|v_i - v_j\right|^{-\gamma} \text{if } v_i - v_j \leq \bar{v}_f;\ \ \forall i \neq j; v_i \neq v_j \text{and } v_i < v_j \\ \quad 1 \qquad\qquad \text{if } v_i = v_j \quad \forall i \neq j \\ \quad 0 \qquad\qquad\qquad \text{otherwise} \end{cases} \quad (4)$$

or $\bar{v}_p$ represents another threshold distance beyond which the temporal influence of the past is supposed null, $\bar{v}_f$ represents a threshold distance beyond which the temporal influence relating to anticipation is null and κ represents a scalar that allows less importance to be placed on past and future data than on present data

($\kappa \leq 1$). The temporal function, v_i, makes it possible to establish, according to the time step, the chronology of observations for quarters[7] (Equation 5a) or months[8] (Equation 5b).

$$v_i = 4 \times (yyyy_i - yyyy_{min}) + qq_i \tag{5a}$$

$$v_i = 12 \times (yyyy_i - yyyy_{min}) + mm_i \tag{5b}$$

where $yyyy_{min}$ represents the first year in which observations are available. The form of the general elements provides a generalization of several applications proposed to date, including the structure of Pace *et al*. (1998, 2000) and Smith and Wu (2009).

Supposing that observations are chronologically arranged beforehand, the form of the temporal weights matrix can be broken down according to the triangular sections. Some elements of the upper triangular section can be negative when unit *i* is observed before unit *j*. For this reason the absolute value operator is used in the definition of the general elements of the matrix (Equation 4). The non null and non unitary elements (different from 1) link future observations to present observations. The lower triangular section introduces links that unite past observations to present observations. Lastly, unitary elements of both triangular sections indicate temporal synchrony relations (Line 3 – Equation 4).[9] In the end, the group of general elements that allow all of the observations to be linked among them defines the specification of the spatial weights matrix, **T** notation (Equation 6).

$$\mathbf{T} = \begin{bmatrix} 0 & t_{12} & \cdots & t_{1j} & \cdots & t_{1N_T} \\ t_{21} & 0 & \cdots & t_{2j} & \cdots & t_{2N_T} \\ \vdots & \vdots & \ddots & \vdots & \cdots & \vdots \\ t_{i1} & t_{i2} & \cdots & t_{ij} & \cdots & t_{iN_T} \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ t_{N_T1} & t_{N_T2} & \cdots & t_{N_Tj} & \cdots & 0 \end{bmatrix} \tag{6}$$

Construction of the matrix is determined exogenously. Evidently, one of the challenges is to establish the parameters pertaining to the optimal threshold distance of expectations, $\bar{v}_f$, and the optimal threshold distance for past observations, $\bar{v}_p$. These values can simply be set by the modeller according to some *a priori*.

Spatio-temporal weights matrix

The spatio-temporal weights matrix, **W**, is obtained by multiplying the elements, term-by-term, of the spatial weights matrix by the temporal weights matrix (Equation 7).

$$\mathbf{W} = \begin{bmatrix} 0 & s_{12} \times t_{12} & \cdots & s_{1j} \times t_{1j} & \cdots & s_{1N_T} \times t_{1N_T} \\ s_{21} \times t_{21} & 0 & \cdots & s_{2j} \times t_{2j} & \cdots & s_{2N_T} \times t_{2N_T} \\ \vdots & \vdots & \ddots & \vdots & \cdots & \vdots \\ s_{i1} \times t_{i1} & s_{i2} \times t_{i2} & \cdots & s_{ij} \times t_{ij} & \cdots & s_{iN_T} \times t_{iN_T} \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ s_{N_T1} \times t_{N_T1} & s_{N_T2} \times t_{N_T2} & \cdots & s_{N_Tj} \times t_{N_Tj} & \cdots & 0 \end{bmatrix} \tag{7}$$

This operation can be summarized using a matrix operator: the Hadamard product (Equation 8).

$$\mathbf{W}_{(N_T \times N_T)} = \mathbf{S}_{(N_T \times N_T)} \odot \mathbf{T}_{(N_T \times N_T)} \tag{8}$$

This type of matrix ensures that spatial relations are considered only when it takes shape during the same period. Multidirectional spatial relations are divided on each side of the main diagonal, composed of null elements. The form of the matrix also makes allowance for the unidirectionality of spatial effects that arise at different time periods. The lower triangular section makes allowance for spatial unidirectional relations. Clearly, multidirectional components can also consider a given time lag for which the temporal proximity is close enough to suggest quasi-simultaneity. Lastly, the spatio-temporal matrix considers possible anticipation relationships. The upper triangular section indicates these relationships. In the end, the shape of the spatio-temporal weights matrix allows spatial and temporal constraints within a unique shape to be respected.

A spatio-temporal matrix can, as is usually the case with spatial weights matrices, be row-standardized and used to detect spatial autocorrelation patterns over time (Dubé and Legros, 2013a), to estimate spatial autoregressive coefficients while controlling for the temporal dimension (Dubé *et al.*, 2013b) or to estimate spatially localized dynamic effects (Dubé and Legros, 2011, 2013b). Standardisation works the same way as for the spatial matrix (see Equation 3).

Empirical Applications

Empirical applications endeavour to establish whether the use of spatial weights matrices, as opposed to spatio-temporal weights matrices, overestimates the spatial effect in the context where individual spatial observations are collected over time. More specifically, the applications focus on testing three hypotheses:

1) spatial autocorrelation detection tests are systematically biased in favour of rejecting the null hypothesis of no spatial autocorrelation, in a spatio-temporal context, when spatial weights matrices are used;
2) estimated autoregressive coefficients in spatial econometric models are greater when spatial weights matrices are used rather than spatio-temporal weights matrices, given that the spatial dependence measured is greater; and
3) spatio-temporal weights matrices allow the generation of new variables that capture a dynamic effect that proves significant.

The last hypothesis helps to improve and perfect the modelling in order to account for the concept of “comparables,” which is similar to the concept of “peer effects,” widely recognized in education economics and labour economics.

The applications include past work and provide a summary of the results obtained to date in order to track various common trends. A comparison of the results also allows to evaluate, in light of the results and comparisons, the impact of using a strictly spatial modelling approach in a context where data consists of a collection of individual spatial layers pooled over time. The empirical examples are based on cities where the data base is easily available for estimation: Quebec (Canada), Paris (France) and Lucas County (United States).

The case of Québec (Canada)

Data for applications concerning Quebec City come from an empirical application aimed at assessing the impact of comparables in determining real estate market values (Des Rosiers *et al.*, 2011). In their study, the authors look at single-family residential transactions recorded in the Quebec City region (including de-merged cities) between April 1990 and December 1996.[10] The database contains 15,729 transactions, and each observation indicates the nominal sales price (in Canadian dollars)[11] and a list of physical[12] and environmental[13] residential characteristics, such as accessibility to the closest services (Des Rosiers *et al.*, 2000). In addition, the City is subdivided into seven (7) sub-markets (Voisin *et al.*, 2010) to control for various fixed effects linked to location that influence the determination of values, but whose identification of the effect source is likely historical. Consequently, these fixed effects variables in part control the issue of spatial autocorrelation (Dubé *et al.*, 2011c).

This initial analysis seeks to verify the first hypothesis, whether omitting the time dimension has an impact on the over-evaluation of the spatial dependence pattern among hedonic price equation residuals. The results suggest that the use of a spatial weights matrix in a spatio-temporal context overestimates the spatial dependence pattern among observations, regardless of the type of matrix selected and the hedonic price model specification (Table 1). In spite of the overestimation of the effect of spatial dependence, the results nevertheless show that a pattern of spatial dependence is significant even when considering the temporal dimension. An initial discovery is that it is not enough to consider the temporal dimension in order to fully control the spatial autocorrelation issue for error terms. These results support the preceding findings of Dubé and Legros (2013a). However, they reveal the importance of accounting for the temporal dimension in the calculation of spatial dependence.

INSERT TABLE 1 HERE

Evidently, the overestimation of the spatial dependence pattern can also hide another problem: that of the overestimation of estimated autoregressive coefficients in autoregressive spatial models. This hypothesis is impossible to ignore in the case of the Quebec City data (Table 2). Thus, the autoregressive coefficient estimated using the spatio-temporal approach is weaker, by 25 per cent, than that obtained using the spatial approach. Moreover, the variables pertaining to the environmental characteristics are highly more significant, suggesting that a strictly spatial approach diminishes the effect of variables on the determination of the selling price. This last conclusion is important for searchers who try to isolate the effects of extrinsic amenities related to land and urban planning policies. In fact, if the results for Quebec are generalized to all other cases, these results imply that using a spatial autoregressive model for evaluating the marginal mean effect of environmental characteristics on house prices may in fact underestimate the significativity of the effect, as well as potentially underestimate the effect. Note that this conclusion can be even more pronounced if one uses a spatial autoregressive model (SAR) instead of a spatial error model (SEM).

INSERT TABLE 2 HERE

In short, the applications on Quebec City data reveal the potential danger involved in the overestimation of spatial effect when data consists of spatial units collected continuously over time. What is difficult to establish, at this time, is the possible influence played by the introduction of new explanatory variables based on the creation of spatio-temporal weights matrices and likely to capture a spatialized temporal dynamic effect in the determination of real estate market values. This hypothesis is discussed more formally in the following two empirical applications.

The case of Paris (France)

Dubé and Legros (2011) conducted an application on the city of Paris, including the departments of Paris, Seine-Saint-Denis, Val-de-Marne and Hauts-de-Seine, in order to assess the impact of the addition of spatialized dynamic variables on the determination of apartment sales prices. Data for the transactions come from the "Base d'Informations Économiques Notariales - BIEN" and cover the period from 1990-2001. The database contains information on the nominal sales price of apartments (in euros) and various information on the physical characteristics of the apartments. However, no data on the environmental characteristics of the residences is available. In total, data is available for some 127,787 transactions.

For calculation time purposes, the analyses are conducted by taking three random samples of 10,000 observations in order to verify the robustness of the results obtained. This method also allows the analyses to be conducted without unnecessarily adding to the calculations. The ultimate goal of this analysis was not to develop an entirely new model for predicting real estate values, but rather to verify whether the addition of dynamic variables, measuring the mean sales price taking place within a given radius before a given transaction, has a significant effect on the determination of sales prices. The dynamic variables can be seen as peer effects or the effect of comparables commonly used in professional practice to establish the asking sales price (Des Rosiers *et al.*, 2011).

The analysis also seeks to determine whether the addition of these variables has a significant effect on the reduction of the spatial autocorrelation of residuals since the new variables clearly have a spatial dimension. The first finding of the analysis is that the addition of dynamic variables (peer effects) substantially reduces the measure of the spatial dependence among error terms (Table 3). However, the simple addition of spatialized dynamic variables is not enough to eliminate the overall pattern of dependence. Nonetheless, the addition of two dynamic variables has the effect of reducing the pattern by almost half.

INSERT TABLE 3 HERE

It is thus necessary to introduce a specification that controls for remaining spatial autocorrelation. The standard correction using an autoregressive error term specification also allows the construction of an autoregressive spatio-temporal model: the introduction of dynamic lags of the dependent variable and monitoring of the spatial multidirectional effect by way of a latent specification.

The results suggest that transactions that took place two quarters prior account for approximately 15% of the sales price, thus revealing the importance of this variable in the determination of real estate values (Table 4). However, the temporal effect is relatively concentrated since the addition of a variable that considers transactions occurring between two to four quarters prior is significant, but the magnitude of the coefficient is clearly less, accounting for less than one per cent of the sales price.

INSERT TABLE 4 HERE

The results underline a new phenomenon in evaluating the effect of extrinsic amenities on house prices, since the effect is not only spatial, but can also be amplified by the temporal dimension. The significant and large coefficient related to the dynamic spatially located variable suggests that the effect of new urban and planning policies may not be instantaneous, but can be amplified (negative or positively) over time. Thus, these results may have several implications when one uses a hedonic pricing model to evaluate the effect of a change in environmental amenities over house prices. In other words, the marginal effect is no longer measured only by the coefficient related to given amenities, but now also needs to incorporate the possible spillover effect related to the temporal dynamic effect, as well as the spillover effect related to the spatial effect if one uses a SAR model (see LeSage and Pace, 2009).

In brief, the effect of comparables is statistically significant, but does not in itself mask the importance of individual characteristics of real estate. Instead, it proposes that the effect may be amplified through time. However, it is reasonable to verify whether this conclusion can be generalized with other individual cases. An application on American data allows us to partially verify the robustness of the results.

The case of Lucas County (Ohio, USA)

Data for single-family residential transactions registered in Lucas County in Ohio (United States) come from an empirical application conducted by LeSage and Pace (2004) and are reviewed again for various examples in the recent spatial econometrics reference book of LeSage and Pace (2009) and LeSage (1999). The database is accessible in the MatLab library and provides information on the nominal sales price (in $USD), lot size (sq.ft.), living area (sq.ft.) and other physical characteristics such as the number of rooms, bedrooms, bathrooms, type of residence and presence of garage. Data on the year of construction also indicates the age of the residence. There are a total of more than 25,357 transactions available to conduct the empirical analysis.

The results suggest that the development of a spatio-temporal weights matrix to evaluate the degree of spatial dependence among residuals of the models decreases the importance and significance of detection if we compare it with a specification based solely on a spatial weights matrix (Table 5). In fact, this problem shows that neglecting the temporal dimension of data can lead to an overestimation of the spatial dependence problem, and reconfirms the first hypothesis.

INSERT TABLE 5 HERE

Estimation results show that the variables summarizing the mean sales prices in the neighbourhood are significant on the determination of residential values, both with the ordinary least squares method (OLS) and by correcting for the problem of spatial autocorrelation of residuals in a spatio-temporal context (Table 6). The coefficients and their significance thus confirm the third hypothesis and the results obtained for Paris. In spite of the significance of the spatialized dynamic effects, these variables by themselves do not fully control the spatial dependence process observed among the residuals of the model (OLS model). However, these spatialized dynamic variables can be seen as a natural extension of the spatial autoregression (SAR) model, but where the spatial is temporally lagged.

Since spatial autocorrelation is still detected among residuals, it is necessary to consider a full spatial autoregressive correction method. In other words, the comparable sales variable allows to diminish spatial autocorrelation pattern, but not to totally control for it. This is why an additional spatial term, based on a spatial error model, is introduced in the equation: to adequatly control for remaining spatial autocorrelation and ensure correct interpretation of the estimated coefficients.

The scope of the coefficients adjusted for spatial dependence among residuals suggests a certain temporal concentration of the spatial effect (direct dynamic effect), regardless of spatial distances (column 2). As seen earlier, the solely spatial specification of the weights matrix demonstrates that the autoregressive effect is overestimated, thus confirming the second hypothesis. In fact, in the present context, the scope of the estimated spatial autoregressive coefficient with a strictly spatial weights matrix reports the presence of a unit root, thus introducing the possibility of spurious results (column 3). Added to this problem is the fact that the overestimation of the spatial effect reduces the significance of dynamic effects linked to the mean housing sales prices (comparables) during the previous month.

INSERT TABLE 6 HERE

If the results cannot be generalized to all empirical cases, they clearly suggest that the omission of the temporal dimension can introduce more problems that it can actually solve. The unit root problem introduces a spatial non-stationary process, which could be quite problematic since the effect of such a process remains poorly documented. Moreover, by taking such amplitude, the autoregressive effect may in fact capture something else.

In brief, the results once again confirm the hypotheses raised, that is, that the consideration of spatial and temporal effects diminishes the scope of the estimated spatial autocorrelation, both on detection tests and on the scope of autoregressive coefficients, and that the addition of spatialized dynamic variables plays a significant role in determining residential home sales values. As mentioned earlier, this decomposition may actually have an important implication in evaluating the marginal effect accounting for spatial and temporal spillover effect.

Ultimately, the results clearly underline the importance of simultaneously considering both dimensions, spatial and temporal, and their effects when the data used consist of spatial individual units pooled over time. The development of spatio-temporal weights matrices is a convenient solution in these circumstances and allows one to adequately express the possible data generating process (DGP) of spatial data pooled over time.

Conclusion

The paper intends to verify whether the application of a spatial econometric model on a hedonic pricing model may generate possible bias and problems if one omits to takes into account the fact that individual sales are collected over time. By proposing a simple approach to account for spatial and temporal dimensions in the construction of an appropriate weights matrix, the paper explores the differences that can occur when estimating the hedonic pricing model without explicitly accounting for the temporal dimension.

Given that the structure of the data is clearly different from panel data structure and that spatial approaches developed for panel data cannot easily be transposed to spatial data pooled over time, it is necessary to define a way to process this data. The application of strictly spatial techniques and methods in a context where the spatial data also include a temporal dimension is not the appropriate method. In fact, the use of spatial approaches in a spatio-temporal context has the effect of overestimating the measurement of the degree of spatial dependence among observations, in addition to generating an overestimation of spatial effects in statistical models.

Based on empirical applications for available data on Quebec City (Canada), Paris (France) and Lucas County (USA), the paper intends to test three hypotheses. The first is that the spatial autocorrelation detection test is systematically biased to rejecting the null hypothesis (absence of spatial autocorrelation) when the weights matrix is strictly limited to a spatial context and, by that very fact, ignores the temporal dimension. The second hypothesis is that the use of strictly spatial weights matrices in a spatio-temporal context overestimates the scope of autoregressive coefficients. And the third hypothesis is that the addition of spatially and temporally lagged variables allows the inclusion of the peer effect (comparables effect) that appears to play a significant role in the determination of residential real estate prices.

The results suggest that these hypotheses cannot be disregarded, as concerns the three different applications. Not only does the non-consideration of the temporal dimension upwardly bias the detection measurement of spatial dependence patterns among residuals, it also influences the scope of autoregressive coefficients. Coefficients estimated with a strictly spatial weights matrix always result in higher coefficients than those obtained using a spatio-temporal weights matrix. As well, the creation of spatio-temporal weights matrices also permits the definition of a group of new variables that play a significant role in the determination of real estate sales prices. Creating peer effect or comparable variables is potentially important in explaining sales prices, in spite of the fact that they do not succeed in fully controlling for spatial dependence effect in the examples selected.

Ultimately, the creation of spatio-temporal weights matrices, through a combination of spatial weights matrices and temporal weights matrices, is a way of tweaking existing spatial econometric methods and tests without having to rework their given properties. Thus, modifying weights matrices in a spatio-temporal context becomes important and essential, especially if we consider the possibility of obtaining spatial autoregressive coefficients that display unit root behaviour.

Moreover, the results also suggest that the spatial applications of modelling techniques influence the significativity of the coefficients related to the intrinsic (or environmental) amenities. If these results appear to be generalized to all applications, this conclusion may have several implications if one attempts to correctly measure for the effect of extrinsic amenities on the house price determination process, as is often the case in the hedonic pricing model. Thus, instead of mechanically correcting for possible spatial autocorrelation among residuals of the hedonic pricing model, the results claim that it is of primal importance to account for the data generating process (DGP) since spatial autocorrelation may not always be a "problem" (Legendre, 1993). Another possibility of accounting for spatial autocorrelation among residuals may be to control for this possibility after introducing all important variables in the model (see Dubé *et al.*, 2012).

Notes

1 Anselin (2010) suggests rather that spatial econometrics has been around for some thirty years.

2 In fact, the phenomenon of anticipation is a case where the future partly influences what happens today.

3 Empirical examples are based on the use of current MatLab software estimation (LeSage, 1999) by modifying the form of the weights matrix in order to use observation data in three dimensions: latitude, longitude and time.

4 The total number of observations is defined by the sum of observations on each of the T periods, N_t: $N_T = \sum_{t=1}^{T} N_t \neq NT$.

5 The friction parameter normally has a value of zero (surroundings), of one (inverse distance) or of two (inverse distance squared).

6 See note 5.

7 An observation *i* is thus recorded for year $yyyy_i$ and quarter qq_i.

8 An observation *i* is thus recorded for year $yyyy_i$ and month mm_i.

9 Supposing that the multiplying constant, κ, is less than 1.

10 With the exception of the year 1992, for which no formal transaction records are available.

11 The data selected include properties whose sales price falls between $50,000 and $250,000CDN.

12 These are intrinsic characteristics such as living area, property size, year of construction, number of bathrooms, quality of materials, architectural characteristics, fireplaces, pool, terraces, type of garage, etc.

13 These are extrinsic characteristics such as median revenue for neighbourhood, percentage of single-parent families, university graduates, accessibility to regional or local services, etc.

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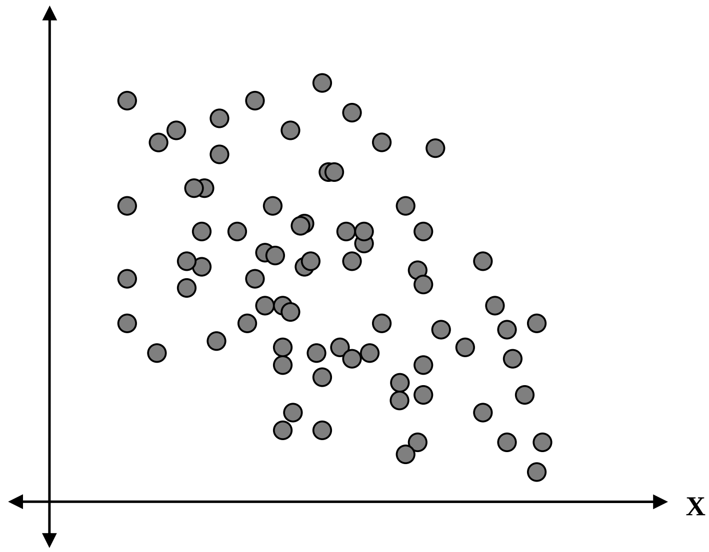
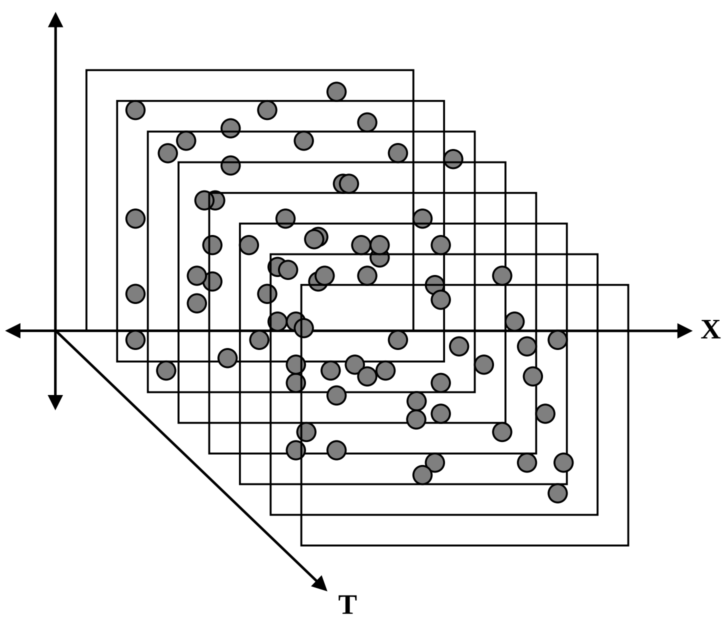


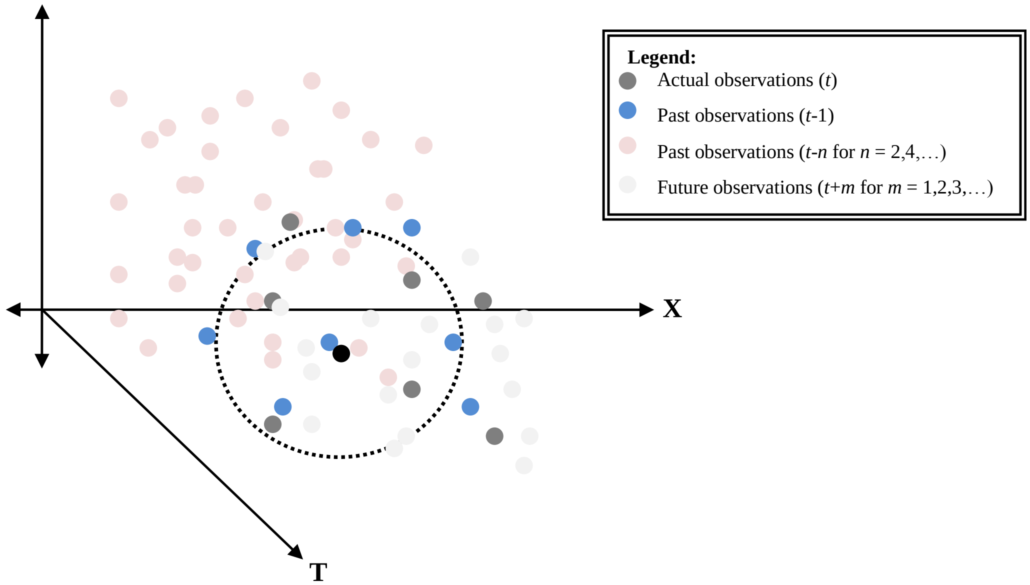
Dubé and Legros (2013b)

Figure 1 - Structuring observations allowing for the calculation of distances and establishment of relationships.



Dubé and Legros (2013b)

Figure 2 - Temporal structuring of individual spatial observations.



Dubé and Legros (2013b)

Figure 3 - Spatio-temporal relations for a given observation

Table 1 - Summary of spatial autocorrelation detection tests according to the type of spatial weights matrix used - Québec, 1990-1996.

	Intrinsic Characteristics	
	Moran's I	***t*-statistic**
Spatial matrix 1 500 m. **($W=S_1$)**	0.3044	21.34
Spatio-temporal matrix 1 500 m. **($W=S_1 \odot T$)**	0.1706	9.88
Spatial matrix 3 000 m. **($W=S_2$)**	0.2865	21.21
Spatio-temporal matrix 3 000 m. **($W=S_2 \odot T$)**	0.1708	9.98
	Intrinsic and Extrinsic Characteristics	
	Moran's I	***t*-statistic**
Spatial matrix 1 500 m. **($W=S_1$)**	0.1736	12.90
Spatio-temporal matrix 1 500 m. **($W=S_1 \odot T$)**	0.0809	5.09
Spatial matrix 3 000 m. **($W=S_2$)**	0.1609	12.78
Spatio-temporal matrix 3 000 m. **($W=S_2 \odot T$)**	0.0819	4.79

Note: Calculations conducted on 10% of the data base (1 569 observations).

Table 2 - Estimation results for the hedonic price model (intrinsic and extrinsic characteristics), Québec, 1990-1996.

	OLS Model		SEM Model (**W** = **S**)		SEM Model (**W** = **S**⊙**T**)	
	Coefficient	*t*-statistic	Coefficient	*t*-statistic	Coefficient	*t*-statistic
Constant	8.9648	222.33	8.9956	1456.70	8.9700	1472.12
Living area (log - m.^{2})	0.4339	58.57	0.4261	64.02	0.4290	68.58
Lot size (log - m.^{2})	0.0752	19.97	0.0802	22.63	0.0830	25.17
Age of building (log)	-0.1033	-66.29	-0.1033	-57.71	-0.1079	-64.45
Cottage	-0.0549	-12.56	-0.0538	-12.23	-0.0545	-13.15
Attached	-0.1548	-23.34	-0.1421	-17.91	-0.1444	-21.04
Quality index	0.1148	22.67	0.1165	22.64	0.1175	23.72
Number of bathrooms	0.0416	14.45	0.0390	13.75	0.0405	14.69
Finished basement	0.0435	14.75	0.0413	14.43	0.0435	15.36
Brick facade (51% and +)	0.0180	5.72	0.0145	4.61	0.0195	6.37
Number of fireplaces	0.0433	14.16	0.0399	13.45	0.0428	14.76
High end flooring	0.0202	6.98	0.0229	8.04	0.0208	7.44
Solid wood staircase	0.0401	10.20	0.0381	9.71	0.0391	10.30
High end kitchen counters	0.0190	0.92	0.0208	1.05	0.0221	1.12
Low lighting	-0.0193	-4.78	-0.0145	-3.56	-0.0166	-4.23
Cathedral ceiling	0.0331	9.31	0.0297	8.23	0.0285	8.25
Central vacuum system	0.0431	9.61	0.0379	8.65	0.0424	9.89
Attached single garage	0.1123	17.86	0.0948	14.78	0.1010	16.58
Attached double garage	0.0920	10.09	0.0879	10.04	0.0873	10.03
Detached single garage	0.0320	6.94	0.0293	6.42	0.0309	6.90
Detached double garage	0.0586	9.30	0.0637	10.38	0.0579	9.66

Table 2 (continued) - Estimation results for the hedonic price model (intrinsic and extrinsic characteristics), Québec, 1990-1996.

	OLS Model		SEM Model (**W** = **S**)		SEM Model (**W** = **S**⊙**T**)	
	Coefficient	*t*-statistic	Coefficient	*t*-statistic	Coefficient	*t*-statistic
Terrace	0.0329	3.33	0.0207	2.11	0.0260	2.75
In-ground pool	0.0908	14.12	0.0916	14.54	0.0885	14.41
Municipal water supply	0.1238	10.94	0.0954	8.64	0.1180	11.46
Local tax rate	-0.0756	-16.52	-0.0737	-13.71	-0.0784	-15.11
Year 1990	*reference*		*reference*		*reference*	
Year 1991	0.0232	5.65	0.0228	4.33	0.0240	4.33
Year 1992	--	--	--	--	--	--
Year 1993	0.0632	15.21	0.0680	18.06	0.0640	11.51
Year 1994	0.0604	14.41	0.0682	17.88	0.0612	10.95
Year 1995	0.0430	9.58	0.0513	12.57	0.0442	7.39
Year 1996	0.0438	8.65	0.0491	10.52	0.0439	6.49
Regional affordability index	0.0535	25.15	0.0563	19.39	0.0563	21.82
Local affordability index	0.0335	17.95	0.0336	13.08	0.0345	15.17
Number of single-parent families	-0.0059	-4.42	-0.0049	-2.90	-0.0047	-3.23
Median household revenue	0.0080	4.70	0.0076	3.68	0.0065	3.62
Percentage of university graduates	0.0058	37.33	0.0057	28.67	0.0056	32.22
λ	--	--	0.3880	87.49	0.2880	48.82
Number of observations	15 729		15 729		15 729	
R^2	0.7666		0.8000		0.7833	
Adjusted R^2	0,7661		0,7996		0,7829	
Log-likelihood	--		13 179,96		12 738,71	

Note: Spatial weights matrix uses the inverse square distance specification using a cut-off distance threshold set at 3,000 metres; the temporal weights matrix is based on transactions occurring in the current quarter.

Table 3 - Summary of autocorrelation detection tests according to model specification with a spatio-temporal weights matrix (**W** = **S**⊙**T**), Paris, 1991-2000.

	OLS Model	
	Moran's I	***t*-statistic**
Sample 1	0.1911	67.74
Sample 2	0.1911	69.96
Sample 3	0.1949	70.90
	OLS Model with dynamic effects	
	Moran's I	***t*-statistic**
Sample 1	0..1036	36..79
Sample 2	0..1136	40..35
Sample 3	0..0926	32..78

Table 4 - Estimation results for the hedonic price model (intrinsic characteristics only). Paris. 1991-2000.

	Sample 1		Sample 2		Sample 3	
	Coefficient	*t*-statistic	Coefficient	*t*-statistic	Coefficient	*t*-statistic
Comparables – two preceding quarters (y_{t-1})	0.1521	56.73	0.1439	56.32	0.1967	56.98
Comparables – two to four preceding quarters (y_{t-2})	0.0065	5.50	0.0079	6.82	0.0085	7.62
Constant	5.1098	295.99	5.2390	310.87	4.6417	158.82
Living area (in m^2 - log)	1.0542	133.41	1.0524	131.47	1.0579	138.30
Presence of elevator	0.0747	10.20	0.0706	9.57	0.0624	8.85
Number of bathrooms (log)	0.2285	15.00	0.2193	14.52	0.2331	15.81
Presence of terrace	0.0953	6.46	0.1432	9.82	0.1092	7.73
Presence of garage	0.0501	6.78	0.0432	5.92	0.0421	5.92
Collective heating	0.0289	2.36	-0.0032	-0.26	0.0053	0.47
Construction before 1850	*reference*		*reference*		*reference*	
Construction between 1850 and 1913	-0.0449	-2.96	-0.1025	-6.43	-0.0920	-6.21
Construction between 1914 and 1947	-0.0545	-3.36	-0.1043	-6.18	-0.0908	-5.80
Construction between 1948 and 1969	-0.0869	-5.35	-0.1356	-8.07	-0.1139	-7.29
Construction between 1970 and 1980	-0.0733	-4.31	-0.1168	-6.60	-0.1067	-6.50
Construction between 1981 and 1991	0.0541	2.72	0.0043	0.21	0.0178	0.94
Construction between 1992 and 2000	0.2393	12.4	0.2097	10.56	0.2089	11.26
Located on ground floor	*reference*		*reference*		*reference*	
Located on first floor	0.0573	4.75	0.0753	6.23	0.0606	5.23
Located on second floor	0.0812	6.71	0.0967	8.10	0.0905	7.83
Located on third floor	0.0894	7.29	0.1146	9.42	0.0871	7.48
Located on fourth floor	0.0906	7.18	0.1165	9.15	0.0934	7.77
Located on fifth floor or higher	0.0690	5.81	0.0903	7.67	0.0698	6.16

Table 4 (continued) - Estimation results for the hedonic price model (intrinsic characteristics only). Paris. 1991-2000.

	Sample 1		Sample 2		Sample 3	
	Coefficient	*t*-statistic	Coefficient	*t*-statistic	Coefficient	*t*-statistic
Seine-Saint-Denis	*reference*		*reference*		*reference*	
Paris	0.5829	36.34	0.5946	39.33	0.5593	37.90
Hauts-de-Seine	0.3896	23.23	0.4041	25.23	0.3505	22.68
Val-de-Marne	0.2061	11.64	0.1847	10.84	0.1849	11.28
Sold in 1990	*reference*		*reference*		*reference*	
Sold in 1991	-0.0198	-1.00	-0.0440	-2.25	-0.0418	-2.19
Sold in 1992	-0.0890	-4.73	-0.0947	-5.20	-0.0993	-5.58
Sold in 1993	-0.1687	-9.05	-0.1624	-8.84	-0.1785	-9.82
Sold in 1994	-0.1675	-9.20	-0.1828	-10.23	-0.1931	-10.97
Sold in 1995	-0.2159	-11.52	-0.2462	-13.42	-0.2505	-13.70
Sold in 1996	-0.3102	-17.32	-0.3052	-17.23	-0.3133	-17.98
Sold in 1997	-0.3193	-17.56	-0.3202	-17.92	-0.3485	-19.62
Sold in 1998	-0.3129	-17.27	-0.3134	-17.53	-0.3436	-19.71
Sold in 1999	-0.2533	-14.24	-0.2660	-15.14	-0.2831	-16.47
Sold in 2000	-0.1864	-10.18	-0.1857	-10.3	-0.1978	-11.19
Sold in 2001	-0.1281	-6.64	-0.1205	-6.41	-0.1132	-6.09
λ	0.6290	54.59	0.6360	55.25	0.6070	45.16
R^2	0.8220		0.8249		0.8396	
Adjusted R^2	0.8214		0.8244		0.8391	

Note: Spatial weights matrix using the 15 nearest neighbours and temporal weights matrices for the current quarter and the preceding year.

Table 5 - Summary of spatial autocorrelation detection tests according to model and weights matrix used. Lucas County. Ohio (USA). 1993-1998.

	OLS Models	
	Moran's I (W= S⊙T matrix)	***t*-statistic**
Intrinsic characteristics	0.2234	77.50
Direct dynamic effects	0.2180	75.70
Direct and indirect dynamic effects	0.2152	74.72

	OLS Models	
	Moran's I (S matrix)	***t*-statistic**
Intrinsic characteristics	0.3240	36.79
Direct dynamic effects	0.3084	321.56
Direct and indirect dynamic effects	0.3052	318.44

Note: The spatial weights matrix is based on an inverse square distance matrix using a 500-metre distance cut-off; the temporal weights matrix considers sales that took place during the same month.

Table 6 - Estimation results for the hedonic price model (intrinsic characteristics only). Lucas County. Ohio (USA). 1993-1998.

	OLS Model		SEM Model (**W** = **S**⊙**T**)		SEM Model (**W** = **S**)	
	Coefficient	*t*-statistic	Coefficient	*t*-statistic	Coefficient	*t*-statistic
Constant	3.1131	41.29	3.6054	49.94	3.7151	5.86
Age (in years - log)	0.4603	60.12	0.0341	43.33	0.0327	40.92
Age (in years)	-0.0219	-103.91	-0.0164	-74.33	-0.0133	-59.92
Living area (in ft^2 - log)	0.6191	61.96	0.6473	95.01	0.6306	77.64
Lot size (in ft^2 - log)	0.2138	54.68	0.1714	72.72	0.1140	29.51
Number of bathrooms	0.1006	14.19	0.0939	16.40	0.0716	13.22
With or without garage	0.3356	44.51	0.2521	38.36	0.1815	31.67
Home with two or more stories	0.1930	31.94	0.1358	26.23	0.0848	17.65
Sale in 1993	*reference*		*reference*		*reference*	
Sale in 1994	0.0049	0.51	-0.0066	-0.28	0.0303	4.30
Sale in 1995	0.0458	4.88	0.0113	0.49	0.0749	10.80
Sale in 1996	0.0790	8.63	0.0358	1.59	0.0991	14.64
Sale in 1997	0.1132	12.45	0.0780	3.49	0.1415	21.00
Sale in 1998	0.1603	17.21	0.1314	5.72	0.1922	27.91
Dynamic effect one month prior[ϡ] (1000 metres)	0.0225	12.09	0.0088	4.57	-0.0002	-0.15
Dynamic effect two months prior[ϡ] (1000 metres)	0.0190	11.16	0.0157	7.99	0.0027	2.11
Dynamic effect three months prior[ϡ] (1000 metres)	0.0116	7.61	0.0106	5.52	0.0012	1.10
Dynamic effect one month prior [ɣ] (2000 metres)	-0.0164	-7.19	-0.0017	-0.71	0.0035	1.99
λ	--	--	0.6830	171.78	0.9900	133.91

Table 5 (continued) - Estimation results for the hedonic price model (intrinsic characteristics only). Lucas County. Ohio (USA). 1993-1998.

	OLS Model		SEM Model (**W** = **S**⊙**T**)		SEM Model (**W** = **S**)	
	Coefficient	*t*-statistic	Coefficient	*t*-statistic	Coefficient	*t*-statistic
R^2	0.7392		0.7960		0.8584	
Adjusted R^2	0.7390		0.7959		0.8583	
Log-likelihood	---		-1 055.01		4 124.72	
Number of observations	25 357		25 357		25 357	

Legend:

ჯ: Transactions within a radius of 1.000 metres

ɣ: transactions within a radius of 2.000 metres

Note: Spatial weights matrix is based on an inverse square distance specification using a critical cut-off distance value fixed to 500 metres; the temporal weights matrices designed observations occurring for the current month for spatial autoregressive effect.