SPATIAL EFFECTS IN HOUSING PRICE MODELS

DO HOUSING PRICES CAPITALIZE URBAN DEVELOPMENT POLICIES IN THE AGGLOMERATION OF DIJON (1999) ?

Catherine Baumont

LEG (CNRS UMR 5118) et MSH
Université de Bourgogne

Pôle d'Economie et de Gestion
B.P. 26611, 21066 Dijon Cedex
France

e-mail: catherine.baumont@-bourgogne.fr

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Abstract

In this article we suppose that the integration of accessibility and neighborhood variables in hedonic housing models doesn't allow to take into account the spatial effects between the housing prices. Using a sample of 1520 transactions of apartments in the urban area of Dijon, we focus on two types of location variables : the distance to the CBD and the distance to several Disadvantaged Districts located in peripheral areas. We detect the presence of a spatial error autocorrelation in the hedonic model indicating that the valuation of the price of an apartment is locally influenced by the prices of the neighboring apartments. Then, we estimate a spatial error model which shows that the local effect is positive and significant and that the location variables remain significant : housing prices are positively influenced by the accessibility to the CBD but are negatively influenced by the proximity to a D-District.

Keywords : disadvantaged districts, hedonic models, housing prices, spatial econometrics, urban development policies

Résumé

L'objectif de cet article est de montrer comment l'influence du voisinage peut être intégrée dans les modèles hédoniques de prix immobiliers. Deux approches complémentaires sont utilisées. Des variables explicatives d'accessibilité au CBD, d'appartenance aux quartiers sensibles et de proximité aux quartiers sensibles sont intégrées dans les spécifications hédoniques que nous estimons : les effets "globaux" de ces variables peuvent donc être appréciés. Nous estimons ces modèles hédoniques en tenant compte des effets de dépendance spatiale susceptibles d'exister entre les prix des propriétés voisines : un effet local de voisinage est alors supposé sous la forme d'une autocorrélation spatiale dans les modèles hédoniques estimés. Cette démarche est appliquée à un échantillon de 1520 transactions d'appartements sur la Communauté de l'Agglomération Dijonnaise en 1999 et permet de montrer qu'un effet de dépendance spatiale existe entre les prix immobiliers : le modèle hédonique approprié à estimer est un modèle spatial avec autocorrélation des erreurs. Cet effet spatial existe alors même que les variables explicatives d'accessibilité au CBD et de proximité avec les quartiers d'habitat social sont intégrées dans le modèle hédonique. Nous montrons que l'effet spatial local est positif et que les prix des appartements décroissent quand la distance au CBD augmente, que l'appartenance à un quartier d'habitat social déprécie ces prix et que la proximité à un tel quartier a également un effet négatif sur les valeurs des transactions.

Mots Clés : modèles hédoniques, économétrie spatiale, prix immobiliers, quartiers sensibles, politiques urbaines

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1. INTRODUCTION

Hedonic models have been used widely for estimating housing values depending on a large set of housing attributes and generally grouped in three subsets : 1/ *structural variables* describing housing physical characteristics, 2/ *neighborhood or environmental variables* depicting the quality of amenities and the economic and social characteristics of the housing neighborhood and 3/ *accessibility variables* including distances to major employment centers, to major amenities (recreation and shopping facilities, particular sites, major public utilities…), to road infrastructures and transport access (railway stations, subway stations, major streets, highways, airports…).

Hedonic housing price equations are mainly estimated to produce the best relevant evaluation of the housing price distribution and of the implicit price of each attribute in order to obtain the best reliable forecasts. These estimations are major inputs in the investigation of housing market by the construction of house price indices and by the analysis of consumer demand for attributes. As indicated by the abundant literature on hedonic housing price models, such studies find numerous applications in business, economic and social fields linked to real estate investment decisions, mortgage markets, housing policies and programs, local tax policies, urban environmental planning and urban development.

The precision and the reliability of the estimations are affected by many factors including the selection of attributes, the functional form of the hedonic function, the econometric techniques used and statistical assumption on the dependant variable, on the explanatory variables and on the random error terms (Sheppard, 1997). In this paper, we focus on the way that urban housing value models and their econometric estimations are affected by spatial effects. Spatial autocorrelation and spatial heterogeneity, for instance, are effects known to result in a number of estimation problems : the presence of spatial autocorrelation yields inconsistent and inefficient OLS estimators and spatial autocorrelation often jointly occurs with spatial heterogeneity in spatial processes (Anselin, 1988, Anselin, 2001).

Hedonic models of housing prices are concerned by spatial effects with at least three major reasons.

- Housing is a durable good with a fixed location. First, according to theoretical urban economic models, the housing equilibrium location depends on the accessibility to the major economic center (CBD) and housing prices decrease as the distance to the CBD increases. Second, the real estate property capitalizes the amenities in its neighborhood and its price may be affected by neighborhood developments and changes. Then, real estate properties within the same neighborhood capitalize shared location amenities: neighborhood characteristics and proximity externalities. Third, houses and buildings within a neighborhood have often been built at the same time and tend to have similar structural characteristics. As a result, housing prices could be spatially autocorrelated.
- Spatial heterogeneity may occur if, for example, the coefficients are different depending either on the distance from the CBD (considering an isotropic or an anisotropic space), or on a spatial

regime structure or on other forms of spatial segmentation. In the latter case, the spatial segmentation can be based on the districts of the urban area according to the characteristics of housing (historic or new properties) or to the characteristics of the population (household income, race, rate of unemployment…). In addition, spatial heterogeneity and spatial autocorrelation may be observationally equivalent (Anselin, 2001) when, for example, a spatial cluster of high housing prices in one district and of low housing prices in an other district may be interpreted as heterogeneity between these districts or as a spatial autocorrelation process yielding clusters of similar values. Moreover, we know that spatial autocorrelation in residuals may result from a spatial heterogeneity that is not correctly modeled in the hedonic price equation.

- Many neighborhood and accessibility explanatory variables are difficult to measure because they are unobservable (like the quality of public facilities), complex (the level of criminality or violence, the social and economic composition of a district) or because they depend on the prior identification of major areas and places (CBD and major employment subcenters, major recreational places, major particular sites…) and the way accessibility to them can be measured. In addition, these variable are rarely available in data bases. Even if relevant and reliable data were available, the problem of the identification of the relevant neighborhood boundaries may remain (Dubin, 1992, Basu and Thibodeau, 1998). Selecting the best set of explanatory variables and the correct model specification are also difficult. Then the residuals produced by housing price hedonic models may be correlated due to measurement errors on the variable, omitted variables or other forms of hedonic model misspecifications.

Despite the fact that hedonic housing price models include accessibility or neighborhood variables, which tend to introduce spatial effects into the modelling and estimating processes, only a few empirical studies have applied appropriate econometric techniques to detect and take into account such spatial effects. Taking care of spatial effects means that even when neighborhood and accessibility variables are included as explanatory variables in housing value functions, spatial dependency might remain: spatial econometric estimators provide in that case more reliable inference than OLS estimators. Spatial autocorrelation effects have been modeled in different ways focusing either on spatial models (Anselin, 1988) or on geostatistical models (Dubin, 1992). In the first approach, spatial dependencies in the data or in the residuals are described by an exogenous spatial process whereas they are not based on any had-hoc specification in the second approach. In both cases it is shown that using spatial econometric techniques is better than ignoring the dependencies in the data (Dubin, 1998, Pace and Gilley, 1997, al., 1998). Taking into account spatial autocorrelation improves the estimates and the forecasts on real estate markets, is a substitute of omitted variables or makes it possible to capture spillovers effects and spatial externalities (see for example, Anselin, 2002; Beron and al., 1998; Can and Megboluge, 1998; Dubin, 1992, 1998; Gilley and al., 2001; LeSage, 1996, 1998; LeSage and Pace, 2002; McMillen, 1995[1]; Pace and Gilley, 1997; Tse, 2002). In addition to spatial autocorrelation, the question of spatial

[1] This paper aims at introduce spatial autocorrelation in selection models used to estimate the effect of the land-use zoning policies on land values.

heterogeneity has been widely treated by the use of explanatory variables indicating the existence of housing sub-markets (Basu and Thibodeau, 1998; Wilhelmsson, 2002) or spatial regimes (Páez and al., 2001).

Considering these principles, the aim of the paper is to analyze the spatial distribution of housing prices in the *Communauté de l'Agglomération Dijonnaise* (which is the cornurbation of Dijon, the regional capital of Burgundy in France) and to examine whether spatial effects influence housing prices focusing on the estimation of an hedonic function. More precisely, we are interested in three topics: 1/ studying the spatial characteristics of the housing price distribution in the COMADI, 2/ modelling spatial autocorrelation using spatial econometric specifications (Anselin, 1988, LeSage, 1999) and 3/ estimating the implicit prices of neighborhood and accessibility variables taking care of the spatial residential pattern produced by two different urban development policies, the first one being devoted to a Conservation Area Plan in the core of the COMADI and the second one to social housing programs in peripheral disadvantaged-districts.

The paper is organized as follows. In the following section, we describe the data and the residential patterns of the COMADI. In the third section, we present the spatial weight matrix describing the spatial dependence process and we analyse the spatial pattern of housing prices using exploratory spatial data analysis. We detect some clusters of low housing unit-price values in the disadvantaged-districts while clusters of high housing unit prices tend to be centrally located. In the fourth section, we provide a spatial econometric analysis of hedonic housing price functions including housing attributes, neighborhood characteristics and accessibility variables. More precisely, we estimate a spatial error model and show that the influence of the disadvantaged districts on the housing price values is significant and negative. The paper concludes with a summary of key findings.

2. RESIDENTIAL PATTERNS IN THE COMADI

Our study focuses on a middle-sized French urban area named COMADI (*Communauté de l'Agglomération Dijonnaise*), which is located in the region of Burgundy. A community of agglomerations is composed of several towns adjacent to a major city. It's a kind of large town council. More precisely, the COMADI is composed of 16 adjacent towns: the central city Dijon, which is the capital of Burgundy, and 15 suburban towns: Ahuy, Chenôve, Chevigny-Saint-Sauveur, Daix, Fontaine-lès-Dijon, Longvic, Marsannay-la-Côte, Neuilly-lès-Dijon, Ouges, Perrigny-lès-Dijon, Plombières-lès-Dijon, Quetigny, Saint-Apollinaire, Sennecey-lès-Dijon and Talant. The spatial configuration of the COMADI area is displayed in Map 1[2]. With almost 250,000 inhabitants, the COMADI is the largest French community of agglomerations located between Paris (the largest French conurbation with almost 10 millions people) and Lyon (the second one with almost 2 millions

[2] Maps are created using Arc-View©3.2 software on the basis of maps provided by the *Direction Régionale Bourgogne de l'INSEE.*

people). Moreover, the COMADI can be considered as a conurbation structuring the Metropolitan Area (MA) of Dijon, which is composed of 214 towns in 1999 for a total surface of 561,156 acres and 327,000 inhabitants. The COMADI concentrates 73% of the population of the MA, 86% of the MA employment and more than 90% of the jobs in the tertiary sector. As the strongest urbanized area of its Metropolitan Area, the COMADI concentrates more than 76% of the housing and the concentration is even more important for the apartments (97.2%) than for the single-family homes (50%). Under these conditions, when an household prefers living in an apartment, he simultaneously chooses to live in the COMADI: household's location preferences express the quality of the neighborhood and accessibility characteristics of each location compared to that of the other locations within the COMADI. On the contrary, when the household prefers living in a single-family home, he can choose to live in the COMADI or outside the COMADI: then household's location preferences express the quality of the neighborhood and accessibility characteristics of each location compared to that of the other locations within and outside the COMADI. Since we restrict our study to the COMADI area we attempt to detect whether spatial effects influence the housing prices or not, analyzing the price of houses would be biased. In addition, we know that the single-home family market and the apartment market are characterized by specific attributes. Hence focusing on only one type of housing allows to preserve the homogeneity of the sample.

The data used in our studies are described in the following paragraph. Then we present the major urban development policies implemented by the COMADI for 40 years and we show that they have lead to two specific types of areas: the Conservation Area and the Disadvantaged-Districts.

2.1. HOUSING DATA AND EXPLANATORY VARIABLES

Spatial autocorrelation in housing prices and in hedonic housing price models are studied using data for transactions of apartment sold in 1999 in the COMADI. Housing data are extracted from the file *"Marché Immobilier des Notaires"* provided by the *"Chambre Départementale des Notaires de Côte d'Or".* Since we focus only on sold properties, it is not possible to apply our estimated results without selection bias to the entire distribution of apartment values in the COMADI (LeSage and Pace, 2002). The selection bias results from the fact that the transactions may concern only apartments which have specific characteristics (Tse, 2002). In fact there are about 29,000 houses and 73,500 apartments in the COMADI and total housing transactions concerned 3% of them in 1999 (2,496 transactions of apartments and 687 transactions of single-family homes). Finally our sample contains 1,520 transactions of apartments for which the transaction price and some major structural characteristics are available.

The characteristics of the property are described by the living area, the number of rooms, the address[3], the period of construction (distributed into seven cycles of construction), the number of bathrooms and the presence of a storeroom, of a cellar, of a balcony or of a terrace.

[3] The exact spatial location of each housing (i.e. x and y coordinates) has been calculated from its address. The authors are grateful to Julie Le Gallo and Rachel Guillain for these calculations.

The neighborhood characteristics are measured by census tracts variables available at the IRIS scale (an intra-urban subdivision for statistical information based on population and economic levels[4]). IRIS data are provided by the *Direction Régionale de l'INSEE* (French national statistics institute). The COMADI is divided into 114 IRIS (see Map 1 for a picture of the IRIS scale): at least one transaction occurred in 1999 in 92 of them. Each IRIS can be considered as a sub-market for neighborhood variables associated to the apartment: the population density, the unemployment rate, the percentage of employees, the percentage of middle executives, the percentage of senior executives and professors and the percentage of the foreign population. Let us note that other variables measuring the quality of neighborhood amenities are generally taken into account in housing studies: the distance to the nearest park, the distance to the nearest elementary or primary school, the distance to the nearest junior high school, and the distance to the nearest shopping center. In the COMADI, there are 27 shopping centers, 98 elementary and primary schools, 29 junior high schools and 34 parks. Since the COMADI area is small (42,600 acres), we can consider that all housing are located close to these amenities and public facilities and that including these distance variables would be at best not very significant and would result in multicolinearity problem at worst (Heikkila, 1988).

Map 1: The 114 IRIS of the COMADI

[4] INSEE defines three types of IRIS: residential IRIS, business IRIS and miscellaneous IRIS.

Finally, two types of accessibility variables are considered: the distance to the main economic center (CBD), centrally located in the COMADI, and the inverse distance to the nearest employment subcenter (Table 2b displays the IRIS composition of the CBD and of each employment subcenter).

All variables are presented in Table 1.

Table 1: Variable description

Variable	**Unit**
Structural attributes	
PX (transaction price)	€ (before tax)
SURF (living area)	Square meters
ROOM	Number of rooms
BATH	Number of bathrooms
TERBAL	Dummy (=1 if the apartment has a terrace or a balcony and 0 otherwise)
CELSTO	Dummy (=1 if the apartment has a cellar or a storeroom and 0 otherwise)
BEF1850 (built before 1850)	Dummy (=1 if the apartment was built before 1850 and 0 otherwise)
ANaiaj (built between ai and aj)	Dummy (=1 if the apartment was built between year ai and year aj and 0 otherwise).
AN5013	
AN1447	
AN4869	
AN7080	
AN8191	
AFT1991 (built after 1991)	Dummy (=1 if the apartment was built after 1991 and 0 otherwise).
Neighborhood Variables (measured at the IRIS scale)	
UNEMP (unemployment rate)	%
PSEXEC	% of senior executives and professors
PMEXEC	% of middle executives
PWK	% of employees
FOREIGN	% of foreign inhabitants
DPOP (population density)	Nb of inhabitants per acre
Neighborhood Variables (urban development districts)	
D-District (Disadvantaged District)	Dummy (=1 if the apartment is located in a D-District and 0 otherwise)
MinD-D	Distance to the nearest D-District
C-AREA (Conservation Area)	Dummy (=1 if the apartment is located in the Conservation Area and 0 otherwise)
Accessibility Variables	
DCBD	Distance to the CBD (in meters)
INV-MINSUB	Inverse distance to the nearest employment subcenter (in meters)

Let us note that to avoid multicollinearity problems, we don't consider the accessibility to the railway station since it is centrally located in the CBD. Neither do we consider accessibility to highways since we study housing values in the urban area bordered by these highways. Another reason to neglect accessibility to major infrastructure networks is that the COMADI area is small and that only a small part of the population living in the COMADI works outside the COMADI (11,6%): commuting outside COMADI isn't time consuming.

On average, a apartment in the COMADI is sold 64,575 Euros but the deviation from the mean is relatively high (s= 35,959). The smallest apartment has 11 square meters of living area and the largest one has 306 square meters. The average unit price is 1,042 Euros per square meters (σ = 274). The sub-markets are not of equal size since the number of sales by IRIS varies from 1 to 51 transactions: 33 sub-markets have less than 10 transactions and 31 sub-markets have more than 20 transactions. Oldest sub-markets correspond to IRIS that are centrally located in the COMADI and they naturally have more apartment transactions than peripheral sub-markets where there are more single houses than apartments. 32% of the housing transactions concern apartments built between 1949 and 1969 against 29% for the built period 1970-1980. New apartments represent only 3% of the sample against 6% for the oldest apartments (built before 1850).

Complementary insights of the residential development pattern of the COMADI are drawn from the urban development policies implemented during the second half of the 20th century.

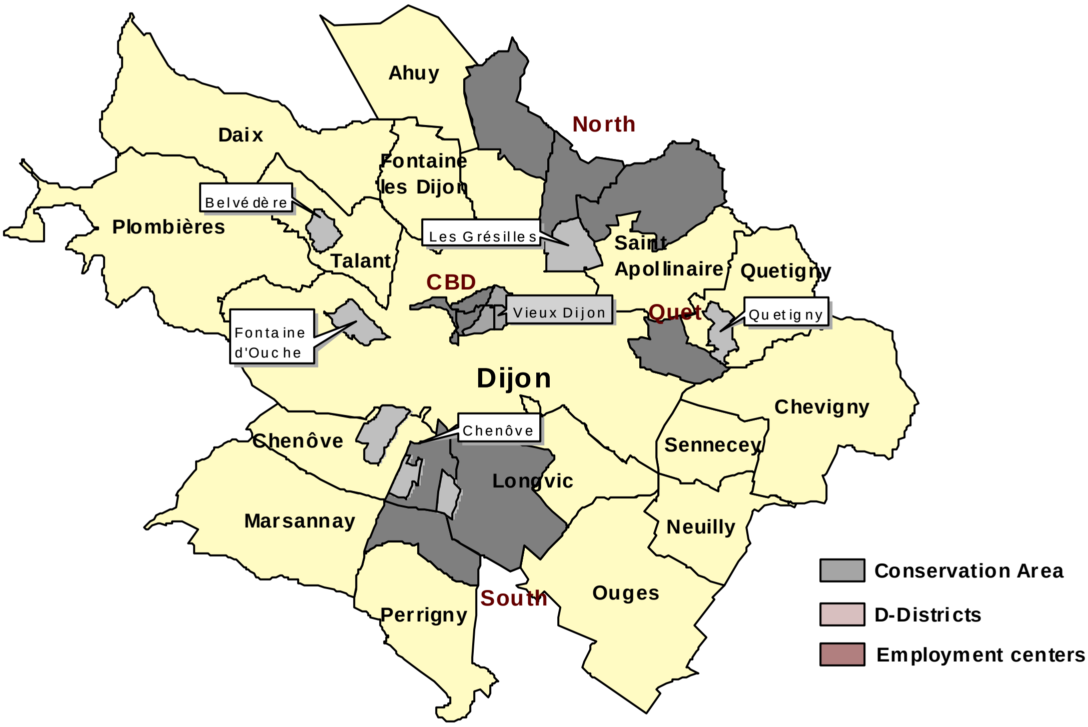
2.2. HOUSING AND URBAN DEVELOPMENT POLICIES IN THE COMADI

Since the beginning of the sixties, two types of urban development policies have structured the spatial residential pattern of the COMADI giving its main current features.

In the sixties and in the seventies, many development operations, sustained by the economic growth and the demographic expansion which had followed the WW2, have been realized where land-use zoning and gigantic proportions were the rule: residential districts in some places, large industrial or commercial areas in other places and major public services and urban amenities in some other places. The urbanized areas doubled in 25 years and two major forms of urban sprawl covered peripheral districts. On one hand, several social housing programs, characterized by high-rise buildings, took place in the districts of "Fontaine d'Ouche" and "Les Grésilles" located in the city of Dijon, in the city of Talant ("Belvédère" district), in the city of Chenôve and in the city of Quetigny. On the other hand, the main industrial and commercial districts were developed in the North, in Chenôve and in Quetigny. It was the beginning of the sub-urbanization of the population and of the emergence of employment subcenters (see Map 2 and Table 2.b).

At the same time, the Conservation and Improvement Area Plan, instituted by the Malraux Law in 1962, has been elaborated and implemented: 295 acres in downtown Dijon are concerned by this plan and it is the largest French conservation area. This area named "Vieux Dijon" nearly corresponds to the medieval town where the major administrative buildings are located (Dijon City Hall, COMADI Council, Regional Council, Prefecture), together with the cathedral Notre Dame and several churches, the covered market and many old buildings with rich architectural features… The conservation area is a mixed area characterized both by high population densities and high employment densities (see Table 2a.). A part of the CBD is located there (see Map 2.).

Map 2: The COMADI
The Conservation Area, the D-Districts and the Employment Centers



The Conservation and Improvement Plan aims at "improving the quality of life in the core of Dijon" following three major guidelines.

1/ To conserve and renovate old buildings respecting their architectural characteristics and to highlight them by the development of their neighborhood.

2/ To improve housing in central areas by the rehabilitation of old buildings (by means of OPAH: Planning Operations for Housing Improvement) and by the construction of new buildings in the spirit of the architectural characteristics of the patrimony. More than 1,200 old apartments have been rehabilitated and 500 new apartments have been built in 15 years.

3/ To develop the cultural and economic attractiveness of downtown Dijon and to improve its accessibility by some specific actions allowing to solve street congestion problems. In the eighties, the city council chose to restrict car traffic flows in the inner streets, to built 5 new parking lots located at the boundaries of the conservation area and to develop urban public transportation. Many streets and public areas were converted into pedestrian areas and pedestrian shopping streets. Terraces of Cafés and pavements now replace outside parking lots. The pedestrian area covers 70% of the conservation area.

The attractiveness of downtown Dijon contrasts with the bad social and economic situation in the social housing districts developed during thirty years in the peripheral districts to face the population growth (see Table 2.a). These districts, hereafter named Disadvantaged Districts (D-Districts) are mainly characterized by a lack of public facilities and stores, a poor quality of environment, a strong degradation of housing, strong parts of immigrant population and of low-income households, a fast growth of criminality and offences… (see Map 2). These problems have lead the urban planners at national, regional and communal scales, to elaborate at the end of the nineties, specific development urban policies for the D-Districts named Urban Renewal Operations and Major Urban Projects in which financial groups like the *Caisse des Dépôts Group* and local banks are strongly implicated. These projects in favor of D-Districts relate mainly to the redevelopment of large-scale social housing complexes by means of demolition, construction and renovation operations, to the supply of public facilities transportation infrastructure and to the promotion of economic activities and job development by means of public subsidies to improve the accessibility and the attractiveness of the urban renewal districts.

Table 2.a
Conservation Area and D-Districts

Conservation Area	**Population** (dens/acre)	**Employment** (dens/acre)
	14,488 (49.2)	8,082 (27.4)
D-Districts	**Population** (dens/acre)	**Employment** (dens/acre)
Chenôve	10,896 (43.9)	508 (2.1)
Fontaine d'Ouche	10,283 (61.5)	660 (4.0)
Les Grésilles	8,239 (28.2)	748 (2.6)
Quétigny	4,820 (34.4)	247 (1.8)
Talant-Belvédère	5,736 (48.6)	206 (1.8)

Table 2.b
Employment Centers

CBD	**Population** (dens/acre)	**Employment** (dens/acre)
	5,799 (33.7)	9,644 (56.0)
Subcenters	**Population** (dens/acre)	**Employment** (dens/acre)
South subcenters	422 (0.2)	11,540 (4.5)
North Subcenter	320 (0.1)	9,634 (3.7)
Quetigny	204 (0.5)	4,014 (8.8)

Using the set of neighborhood variables previously described and supplemented by census housing data available at the IRIS scale, different characteristics of the D-Districts and of the Conservation Area can be underlined (Table 3)[5]. First we can note that some opposite features characterized the Conservation Area, on one hand, and the D-Districts, on the other hand. For example, the Conservation Area is characterized by an high percentage of senior executives and professors (28,4% against 15,8% for the COMADI and less than 7% for the D-Districts), a low percentage of employees (22% against 31% for the COMADI and more than 32% for the D-Districts), a very low ratio of foreign people (4,7% against more than 8,7% and rising up to 17,6% in the D-Districts), a high percentage of old buildings and apartments (82% of the apartments have been built before 1949) and a very low percentage of social housing (5,3% against 22% for the COMADI, more than 51% and rising up to 78% for the D-Districts). The Conservation Area concentrates a large part of the employment whereas the D-Districts are poorly developed. Second, the two types of areas have similar characteristics: high population densities (50 inhabitants per acres on average against less than 6 inhabitants per acres for the COMADI), similar percentages of middle executives (which are lower on average than those observed for the COMADI) and similar rates of unemployment (10% on average excepted for the D-District in Chenôve which is higher: 19%).

[5] Detailed figures are available upon request from the author.

Table 3. Conservation Area and D-Districts : main features

Characteristics	Conservation Area	D-Districts Lowest	D-Districts Highest	COMADI
PSEXEC (%)	28.4	4.1 (Chenôve)	6.9 (Belvédère)	15.8
PMEXEC (%)	27.7	14.3 (Chenôve)	21.2 (Belvédère)	27.1
PWK (%)	22.1	32 (Grésilles)	41.9 (Belvédère)	31.2
DPOP (per acre)	49	28 (Grésilles)	62 (Fontaine d'Ouche)	6
FOREIGN (%)	4.7	8.4 (Quetigny)	17.6 (Grésilles)	5.8
UNEMP (%)	9.9	7.5 (Quetigny)	18.8 (Chenôve)	11.7
DCBD (meters)		2,700 (Fontaine d'Ouche)	5,000 (Quetigny)	
Apartments (%)	71.2	72.6 (Grésilles)	91.9 (Quetigny)	
Vacant housing (%)	13.4	2.5 (Belvédère)	16 (Grésilles)	7.6
Social apartments (%)	5.3	51 (Fontaine d'Ouche)	78 (Les Grésilles)	22.2
Major built period (year and %)	Before 1949 (82%)		Chenôve (AN49-74, 95%), Fontaine d'Ouche (AN49-74, 89%) Grésilles (AN49-74, 77%) Quetigny (AN49-74, 49%), Belvédère (AN75-81, 97%)	

Since housing prices may capitalize location characteristics and spatial externalities it would be interesting to highlight the potential influence of D-Districts, on one hand, and of the Conservation Area, on the other hand, on the housing price distribution in the COMADI. For that purpose, we consider two additional neighborhood variables indicating whether the apartment is located in a Disadvantaged-District or in the Conservation Area (see Table 1). Some studies interested in this purpose (for example, Johnson and Ragas (1987) analysed the impact of the historical area on the land values in the New Orleans CBD) but without taking the impact of spatial effects into account. The spatial statistical tools used to examine these features are presented in the following paragraphs.

3. EXPLORATORY SPATIAL ANALYSIS OF THE HOUSING PRICE DISTRIBUTION

Patterns of local spatial association describing spatial autocorrelation and spatial heterogeneity which may characterized the price distribution of the apartments in the COMADI are analysed by the means of Exploratory Spatial Data Analysis (ESDA).

3.1. THE SPATIAL WEIGHT MATRIX

For studying spatial dependency in housing price distribution and in hedonic housing price equations, it is necessary to incorporate a spatial structure, the well known W weight matrix, exogenously defined, which quantifies the way that an observation at one location depends on other observations at a number of other neighboring locations: it is based on the existence of spillover effects between observations. Each apartment i is connected to a set of neighboring apartments j according to a spatial pattern defined exogenously. The elements w_{ii} on the diagonal are set to zero whereas the elements w_{ij} indicate the way the unit i is spatially connected to the unit j.

These elements are non-stochastic, non-negative and finite. In order to normalize the outside influence upon each unit, the weight matrix is standardized so that the elements of a row sum up to one. Several types of spatial structure can be used: contiguity, nearest neighbors, distance-based functions. Since distance variables are included as explanatory variables, using a distance-based *W* matrix (such as an inverse distance *W* matrix) could produce some kind of multicollinearity between the spatial structure and the explanatory variables that makes interpretation and inference problematic (Wilhelmsson, 2002). Hence we prefer describing the spatial structure by a *k*-nearest neighbors *W* matrix.

The general form of a *k-nearest neighbors* weight matrix *W*(*k*) is defined as follows:

$$\begin{cases} w_{ij}^*(k) = 0 \text{ if } i = j, \forall k \\ w_{ij}^*(k) = 1 \text{ if } d_{ij} \le d_i(k) \\ w_{ij}^*(k) = 0 \text{ if } d_{ij} > d_i(k) \end{cases} \quad \text{and} \quad w_{ij}(k) = w_{ij}^*(k) / \sum_j w_{ij}^*(k)$$

where $w_{ij}(k)$ is an element of the standardized weight matrix and $d_i(k)$ is a critical cut-off distance defined for each unit *i*. More precisely, $d_i(k)$ is the k^{th} order smallest distance between unit *i* and all the other units so that each unit *i* has exactly *k* neighbors. To choose the number of nearest neighbors, we have applied the following procedure. We have estimated by OLS the hedonic housing price functions used in the paper. We have tested the presence of spatial autocorrelation by the means of Moran's I statistic using *N* matrices of *k*-nearest neighbors (*N* varying from 1 to 20), It appears that the value of the statistic reached a maximum for *N* = *7*. Then we choose the spatial *W* matrix corresponding to *k* = 7 nearest neighbors.

3.2. SPATIAL AUTOCORRELATION IN THE HOUSING PRICE DISTRIBUTION

Considering the distribution of housing unit prices (measured in € per square meters), two types of spatial association are tested: global spatial autocorrelation and local spatial association.

If we consider global spatial autocorrelation, which is usually based on Moran's *I* statistic (Table 4.)[6], it appears that housing unit prices are positively spatially autocorrelated at p = 0.0001 significance level[7]. This result indicates that similar values (high or low) of housing unit price tend to be spatially clustered in the COMADI.

Table 4: Moran's *I* statistics for housing unit price distribution in 1999

Variable	Moran's I	St. dev	St. value	p value
Housing unit price*	0.3696	0.0128	28.93	0.0001

* The expected value for *Moran's I* statistic is $E(I) = -1/(n-1) = -6{,}6 \times 10^{-4}$ (n = 1520)

[6] Computations are done with SpaceStat 1.90 (Anselin, 1999) or Matlab 6.5 using procedures presented in LeSage (1998) and in GEOXP.
[7] Inference is based on the permutation approach with 9999 permutations.

Moran's I is a global measure and doesn't allow to appreciate the local patterns of spatial association, i.e. to detect the presence of clusters of high unit price values or of low unit price values in the COMADI. In addition, some apartments might be sold at a low unit price (resp. high unit price) whereas neighboring apartments were sold at high unit prices (resp. low unit prices), reflecting some atypical spatial associations compared to the global pattern of positive spatial autocorrelation.

Inspection of local spatial associations is carried out by the means of Moran scatterplots and Local Indicators of Spatial Associations (Anselin, 1995, 1996)[8].

In a Moran scatterplot the values of a spatial lag variable Wz are plotted against the values of the variable z. It aims at visualizing four types of local spatial association between an observation and its neighbors, each of them being localized in a quadrant of the scatterplot: quadrant HH refers to an observation with a high[9] value surrounded by observations with high values, quadrant LH refers to an observation with low value surrounded by observation with high values, etc. Quadrants HH and LL (resp. LH and HL) indicate positive (resp. negative) spatial autocorrelation reflecting spatial clustering of *similar* (resp. *dissimilar*) values.

In order to assess the significance of such spatial associations, Local Indicators of Spatial Association (LISA) statistics are computed.

The local version of Moran's *I* statistic for each observation i is written as:

$$I_i = \frac{(x_i - m)}{m_0} \sum_j w_{ij} (x_j - m) \quad \text{with } m_0 = \sum_i (x_i - m)^2 / n \qquad [1]$$

where x_i is the unit price of the observation i; $n = 1520$; m is the mean of the observations and where the summation over j is so that only the unit prices of the neighboring apartments of *i*, defined by the spatial *W* matrix, are included: in our case, the unit prices of its 7 nearest apartments are taken into account for each apartment *i*.

A positive value for I_i indicates spatial clustering of similar values (high or low) whereas a negative value indicates spatial clustering of dissimilar values between a apartment and its neighbors. Due to the presence of global spatial autocorrelation, inference must be based on the conditional permutation approach with 9999 permutations. The *p*-values obtained for the local Moran's statistics are then pseudo-significance levels. Note that inference in this case is further complicated by the problem of multiple comparisons since the neighborhood sets of two spatial units contain common elements (Anselin, 1995; Ord and Getis, 1995). Therefore, the overall significance of 5% is not restricted enough and lower significance levels taking into account the number of multiple comparisons have to be used. The Bonferroni's correction is often suggested and consists in dividing the nominal level of significance α by the number of observations. Since this correction becomes too restrictive as the sample size increases, one can also consider that the

[8] The identification of local patterns of spatial association can also be based on the $G_i(d)$ statistics (Getis and Ord, 1992; Ord and Getis, 1995; Getis and Ord, 2001).
[9] High (resp. low) means above (resp. below) the mean.

number of multiple comparisons depends on the type of *W* matrix used: in the case of a *k* nearest neighbors *W* matrix, the maximum number of multiple comparisons between two observations is *k* and the significance level is obtained by dividing α by *k* (Le Gallo and Ertur, 2003). For the 7 nearest neigbhbors *W* matrix, the pseudo significance level is $p = 0.00714$.

Finally, a Moran significance map combines the information in a Moran scatterplot and the significance of LISA by showing the apartments with significant LISA and indicating by a color code the quadrants in the Moran scatterplot to which these apartments belong.

Applying these tools to the housing unit price distribution leads to the following results (see Table 5.). First, it appears that more than 70% of the prices are characterized by spatial positive local associations (513 apartments in quadrant HH and 553 apartments in quadrant LL) while the other observations are characterized by spatial negative local associations (197 apartments in quadrant HL and 257 apartments in quadrant LH). At the 5% pseudo-significance level, 33% of the observations are still characterized by a local spatial association (185 apartments are significantly HH, 228 apartments are significantly LL, 30 apartments are significantly HL and 52 apartments are significantly LH). Using the Bonferroni's correction, 14% of the observations exhibit significant local associations using at the p= 0.00714 pseudo-significace level and among them 34% are of HH type and 56% are of LL type. These results show evidence of several pockets of low transaction prices or of high transaction prices in the COMADI and the location of the respective apartments are given in two Moran significance maps (Map 3 for HH and HL, and Map 4 for LL and LH).

Table 5: Spatial association patterns (LISA) for 7 nearest neighbors

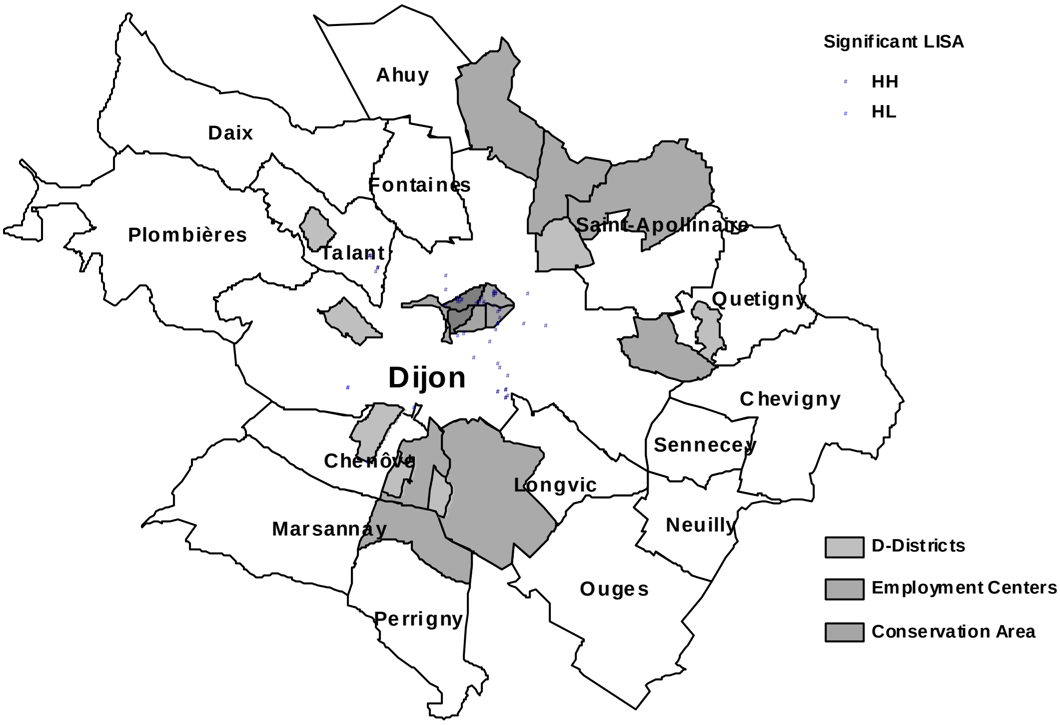
LISA	Nb obs	p = 0.05	p = 0.00714
HH	513	185	71
LL	553	228	116
HL	197	30	7
LH	257	52	14
Total	1520	495	208

Second, we can see that many significant LISA are located either in the Conservation Area or in a D-District. More precisely (see Table 6.), 70% of the significant LISA are located in those areas (48 LISA in the Conservation Area and 98 LISA in a D-District).

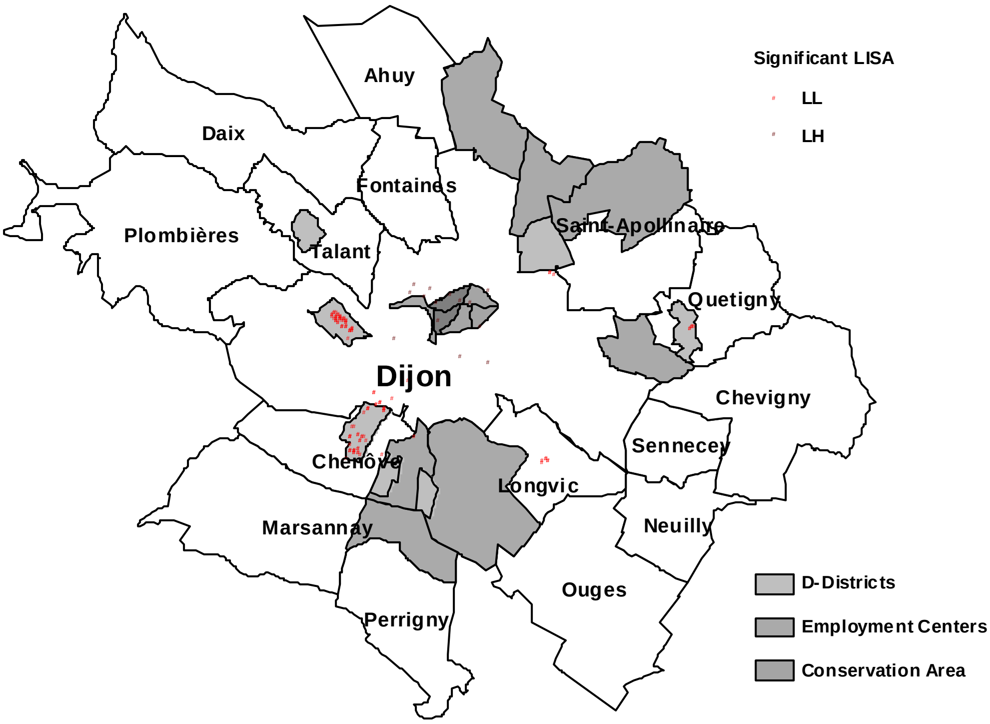
Table 6: Significant spatial association patterns (LISA) in urban development Areas
(*p = 0.00714; 7 nearest neighbors W matrix*)

Areas	HH	LL	HL	LH	Total	Nb. of transactions
CVH	42			6	48	223
D-Districts		96	2		98	178
Other Areas	29	20	5	8	62	1119
Total	71	116	7	14	208	1520

Map 3: Moran significance Map for HH and HL spatial association
(*p = 0.00714; 7 nearest neighbors W matrix*)



Map 4: Moran significance Map for LL and LH spatial association
(*p = 0.00714; 7 nearest neighbors W matrix*)



Given the fact that our sample contains 223 apartments sold in the Conservation Area and 178 apartment sold in the D-District, we can underline that a pattern of significant local spatial association is more often observed in the latter than in the former. Moreover, no apartment located in the D-Districts is of HH type and no apartment located in the core of Dijon is of LL type. On the contrary, almost all the apartments located in a D-District are characterized by a significant spatial association of type LL whereas all the apartments located in the core of Dijon are of HH type or of LH type. Since 67% of the apartment sold there have been built before 1947, this feature possibly reflects bad conditions and the need of renovation. We also note that a local spatial association of HH type also characterizes transactions in areas located outside of the Conservation Area like the areas included in the CBD or located farther from the core of Dijon.

Finally, these results highlight the important role played by spatial effects in the housing price distribution within the COMADI in two ways. First, housing unit prices are positively spatially autocorrelated, which indicates clusters of high (resp. low) housing unit price values in the COMADI. Second, specific neighborhood effects are reflected by the local spatial association patterns and are strongly linked to the D-Districts whereas the role played by the Conservation Area doesn't seem specific.

The estimation of hedonic housing price functions allows us to investigate these points.

4. ESTIMATING RESULTS OF HEDONIC HOUSING PRICE MODELS

Taking into account structural, neighborhood and accessibility variables in hedonic housing price models, allows to evaluate and to test different assumptions. First, we can estimate consumer's willingness to pay for housing attributes and neighborhood quality. Second, we can test at least two urban economic theoretical results. On one handwe expect that in a monocentric urban area, the unit price of housing decreases from the CBD. On the other hand, we expect that in a polycentric urban space, the unit price distribution exhibits a global peak near the CBD and local peaks near secondary employment centers. Moreover, it is generally assumed that the CBD has a global influence on housing price levels whereas employment subcenters compete with each other and have a local influence on these prices. In housing value models, these two levels of influence are distinguished by including the distance to the CBD and by including the inverse distance (or inverse squared distance) to the nearest employment subcenter (see for example, Sivitanidou, 1996). Using Giuliano and Small's (1991) identification method based on employment density and total employment cut-offs, Baumont and Bourdon (2002) identified three employment subcenters: one located in the North, one in the South and the other one in the business district of Quetigny (the IRIS composition of each subcenter is displayed in Table 2b). Using spatial econometrics procedures, Baumont and al. (2003) showed that these subcenters didn't influence the population density distribution in the COMADI. However, it is interesting to study if the housing price distribution, which is a more flexible variable than intra-urban population density distribution, is influenced both by the distance to the CBD and by the distance to these employment subcenters.

Finally, we can be interested in analysing whether the different urban development policies have produced different spatial externalities according to the type of areas the apartment belongs to.

4.1. SPATIAL MODELLING OF HEDONIC HOUSING PRICE FUNCTIONS

Let's take as a starting point the general hedonic housing price model:

$$PX = Aa + Nb + Dg + e \qquad e \sim \mathrm{N}(0, s^2 I) \qquad [2]$$

where *P* is the $(n \times 1)$ vector of the housing prices, *A* is a $(n \times j)$ matrix of structural attributes of the apartment (plus the constant), *N* is a $(n \times t)$ matrix of neighborhoods characteristics, *D* is a $(n \times q)$ matrix of accessibility variables, a, b and g are, respectively, *j*, *t* and *q* length vectors of unknown parameters to be estimated and e is a random error vector with the usual properties.

Following the hedonic modeling literature, we use the log-transformation on the dependent variable and on the explanatory variables (the dummy variables excepted) so that estimated parameters can be interpreted as elasticities. The percentage impact on the housing price of a change in the dummy variable from 0 to 1, is calculated from the corresponding estimated parameter $\hat{d}$ as follows (Halvorsen and Palmquist, 1980): 100*$(\exp(\hat{d}) - 1)$.

Following the spatial econometric literature, two usual spatial models can be specified: a spatial lag model (LAG) and a spatial error model (SEM).

Given the exogenous spatial structure *W*, the spatial lag model is:

$$PX = rWPX + Aa + Nb + Dg + e \qquad e \sim \mathrm{N}(0, s^2 I) \qquad [3]$$

where the estimated parameter r measures the spatial dependence of observations.

The spatial error model is:

$$PX = Aa + Nb + Dg + e \qquad e = lWe + u \qquad u \sim \mathrm{N}(0, s^2 I) \qquad [4]$$

where l is the scalar parameter expressing the intensity of spatial correlation between regression residuals.

Both specifications seem possible *a priori.* In the LAG model, spatial autocorrelation of observations is handled by the endogenous spatial lag variable *WPX* and expresses the fact that the price of an apartment is influenced by the price of the neighboring apartments. In the SEM model, we consider spatial dependence as a statistical nuisance which may occur from various forms of misspecification (omitted variables, the lack of adequate neighborhood measures…).

Ignoring spatial dependence when it is present produces OLS estimators at best inefficient (if model [2] is estimated by OLS whereas [4] is the true model) and at worst biased and inconsistent (if the true model is [3] and [2] is estimated by OLS) (Anselin, 1988). The parameters of both spatial models are generally estimated with the method of Maximum likelihood (ML). In the case that estimates for r or l are significant, spatial autocorrelation may be interpreted as a spatial externality whose intensity depends on the estimated values of the parameters.

Since our aim is to deal with the general impact of spatial dependence in the estimation of hedonic housing price models, we estimate equation [2] by OLS, perform different spatial tests and apply the specification search approach defined by Anselin and Florax (1995) to discriminate between the two forms of spatial dependence[10] (spatial autocorrelation of errors or endogenous spatial lag).

4.2. ESTIMATING RESULTS

In order to focus on the impact of the Conservation Area and of the D-Districts on the housing price values, we include the variables D-District (or MinD-D) and C-AREA in the hedonic functions. To avoid some multicollinearity problems in our estimations, we don't include the variables correlated with these two types of area: AN4869, AN7080, PEXEC, PWK, FOREIGN and DPOP. Neither do we consider AP91 because our sample contains only 41 apartments built after 1991.

Finally, the exploratory variables included in the 3 matrices of housing attributes, neighborhood characteristics and accessibility variables are the following:

A = [LSURF BATH AN5013 AN1447 AN8191 TERBAL]

N = [LPMEXEC D-District (or MinD-D) C-AREA]

D = [LDCBD INV-MinSUB]

where LVAR designs the log transformation of VAR.

To evaluate the influence of the D-Districts, we include either the D-District variable either the MinD-D variable. Instead of the dummy variable D-District, the MinD-D variable allows us to estimate the influence of being located close to a D-District.

Taking the log transformation of the sale price (LPX), the results of estimation by OLS of the complete hedonic model indicates that the number of bathrooms (BATH), the location in the Conservation Area (C-AREA) and the accessibility to the nearest subcenter (INV-MinSUB) are not significant. Then these variables are no more considered and the results of estimation by OLS of the remaining hedonic model are given in the first column of the Table 6.

The model explains 78% of the variation in price and if one were to assume no spatial autocorrelation problem, the results of the OLS estimation suggest the following interpretations. If living area increases by 1%, price will increase by 0.96%. If the percentage of middle executives living in the IRIS where the apartment is located increases by 1%, the price will increase by 0.19%. If the distance to the CBD increases by 1%, then the price will decrease by 0.056%. This result confirms that the accessibility to the major employment center has a strong influence on housing price (let us recall that the distance is measured in meters). This effect probably dominates the influence of the accessibility to an employment subcenter since, as previously noted, the variable

[10] The performance of that approach is experimentally investigated in Florax and Folmer (1992) and in Florax, Folmer and Rey (2003).

related to the distance to the nearest employment subcenter was not significant. The estimates of the parameters associated to the dummy variable indicate that the sale of a apartment built between 1850 and 1913 (resp. between 1914 and 1947) decreases its price by 9.25% (resp. 7.44%) while the sale of a apartment built between 1981 and 1991 increases its price by 22%. Finally, if the apartment is located in a D-District, its price is reduced by 18%. Combining with the fact that D-Districts are located 3.5 kms in average far from the CBD, the location in a D-District strongly depreciates the value of a apartment in the COMADI. Looking at the five spatial tests, it is worth noting that the *Moran's I* test doesn't reject the absence of spatial autocorrelation. We perform the Lagrange Multiplier tests, *LMERR*, *LMLAG* and their robust versions *R-LMERR* and *R-LMLAG* (Anselin, 1988; Anselin *et al.*, 1996) to discriminate between the two forms of spatial autocorrelation: spatial autocorrelation of error or endogenous spatial lag. Applying the decision rule suggested by Anselin and Florax (1995), the results indicate the presence of spatial error autocorrelation rather than a spatial lag: the spatial error model appears to be the appropriate specification of the hedonic housing price function. Therefore, even when some neighborhood and accessibility variables are included, the hedonic housing price function is misspecified due to the omission of spatial autocorrelation of the errors and each observation is not independent of the others. Statistical inference based on OLS estimators is not reliable.

The estimates of the SEM hedonic housing price by ML and by iterated General Method of Moments (GMM)[11] are given in the second and third columns of Table 7. It appears that all coefficients are strongly significant and that a significance positive spatial autocorrelation of the errors is found ($\hat{l} = 0.433$). Furthermore, the LMLAG* test does not reject the null hypothesis of the absence of an additional autoregressive lag variable in the spatial error model. The parameters values are slightly different than in the model estimated by OLS and the strongest variation occurs for the variable D-District. If the apartment is located in a D-District, then its price is reduced by 15%. On the contrary, the influence of the CBD is slightly stronger since the price decreases by 5,8% when the distance increases by 1%. For example, if we consider an apartment built between 1970 and 1980, with a living area of 100 square meters and a balcony, which is located in the D-District of Talant-Belvédère, its estimated price will be 80 127 € using the SEM model against 77 464 € using the OLS model. Considering that spatial effects don't matter in that case leads to under-evaluate the estimated price by 3,44%. Then the influence of the housing urban development policies is highlighted.

Another way to evaluate this influence, is to consider that the negative effect produced by the D-District may spread on the urban area. The estimate of the second hedonic function provides this evaluation by including the variable MinD-D instead of D-District. Since each apartment is characterized by its distance to the closest D-District, a local effect is assumed. The estimated results by OLS are displayed in the fourth column of the Table 7. We can see that the D-Districts produced a significant negative effect on the sale prices : when the distance from a D-District increase, the sale-prices increase too.

[11] We estimate the model by GMM in order to control for the robustness of our estimates by ML for which a normal distribution of the errors is assumed.

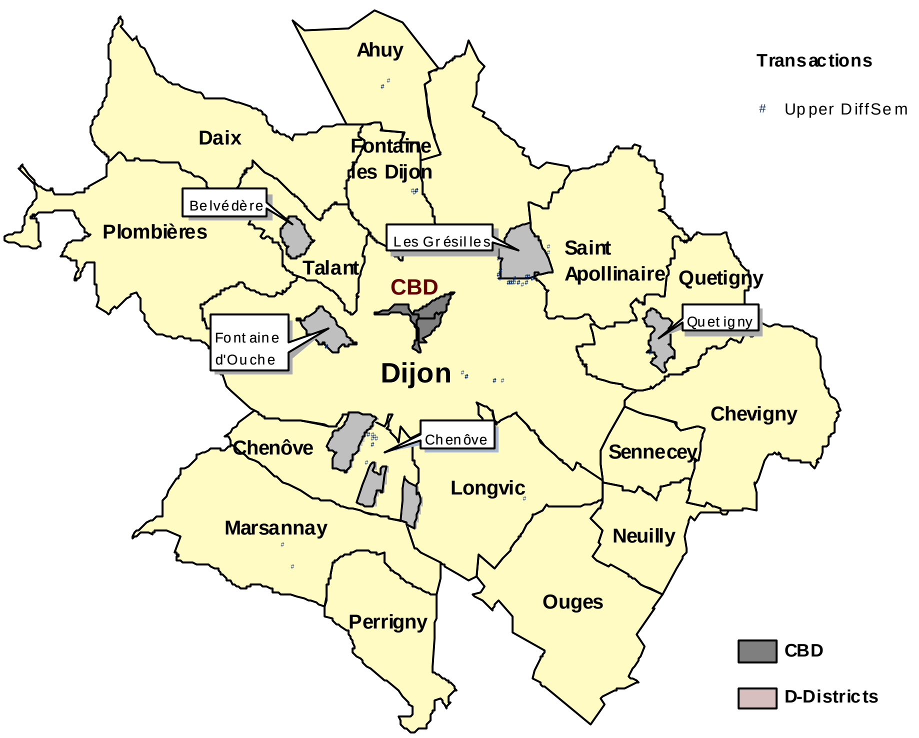
Table 7: Estimates for the hedonic housing price function

Dependent variable		Model 1			Model 2	
LPX	**OLS**	**SEM-ML**	**GMM**	**OLS**	**SEM-ML**	**GMM**
Constant	8.69 (0.000)	8.749 (0.000)	8.753 (0,000)	8.317 (0.000)	8.409 (0.000)	8.413 (0.000)
LSURF	0.964 (0.000)	0.961 (0.000)	0.961 (0.000)	0.963 (0.000)	0.962 (0.000)	0.961 (0.000)
LDCBC	-0.056 (0.000)	-0.058 (0.000)	-0.058 (0.000)	-0.049 (0.000)	-0.044 (0.000)	-0.044 (0.000)
D-District	-0.198 (0.000)	-0.169 (0.000)	-0.169 (0.000)			
MinD-D				$6.663\ 10^{-5}$ (0.000)	$7.305\ 10^{-5}$ (0.000)	$7.273\ 10^{-5}$ (0.000)
TERBAL	0.084 (0.000)	0.084 (0.000)	0.082 (0.000)	0.076 (0.000)	0.08 (0.000)	0.079 (0.000)
AN5013	-0.097 (0.000)	-0.084 (0.000)	-0.085 (0.000)	-0.109 (0.000)	-0.088 (0.000)	-0.089 (0.000)
AN1447	-0.077 (0.001)	-0.083 (0.000)	-0.083 (0.000)	-0.087(0.000)	-0.087 (0.000)	-0.087 (0.000)
AN8191	0.199 (0.000)	0.166 (0.000)	0.166 (0.000)	0.203 (0.000)	0.167 (0.000)	0.167 (0.000)
LPMEXEC	0.197 (0.000)	0.186 (0.000)	0.186 (0.000)	0.253 (0.000)	0.213 (0.000)	0.213 (0.000)
λ		0.433 (0.000)	0.428 (0.000)		0.447 (0.000)	0.444 (0.000)
R²	0.784		0.767	0.783		0.77
R²-adj	0.783			0.782		
Sq.corr		0.783	0.783		0.782	0.783
LIK	-44.142	-125.241		-39.481	-129.190	
AIC	70.285	232.48		60.963	240.379	
BIC	-22.347	-184.544		-13.025	-192.441	
σ^2	0.055	0.049	0.05	0.056	0.049	0.049
Condition number	65.309			65.154		
MORAN	13.753 (0.000)			14.749 (0.000)		
LMERR	178.575 (0.000)			205.702 (0.000)		
R-LMERR	111.301 (0.000)			131.331 (0.000)		
LMLAG or LMLAG*	73.099 (0.000)	6.34* (0.01)		79.497 (0.000)	5.793* (0.016)	
R-LMLAG	5.826 (0.016)			5.129 (0.024)		
LR-error		162.197 (0.000)			179.416 (0.000)	

Notes: *p*-values are in parentheses. SEM-ML indicates maximum likelihood estimation of the spatial error model and SEM-GMM its estimation by the General Method of Moments. Sq. Corr. is the squared correlation between predicted values and actual values. LIK is the value of the maximum likelihood function. AIC is the Akaike (1974) information criterion. BIC is the Schwarz information criterion (1978). MORAN is the Moran's *I* test adapted to OLS residuals (Cliff and Ord, 1981). LMERR is the Lagrange multiplier test for residual spatial autocorrelation and R-LMERR is its robust version. LMLAG is the Lagrange multiplier test for spatially lagged endogenous variable and R-LMLAG is its robust version (Anselin and Florax, 1995; Anselin *et al.*, 1996). LMLAG* is the Lagrange multiplier test for an additional spatially lagged endogenous variable in the spatial error model (Anselin, 1988). LR-error is the likelihood ratio test for the spatial error parameter.

However, let us note that even if it is significant, this impact is local and is smaller than the global effect of the CBD (let us recall that distance is measured in meters in both cases). The spatial tests indicate that a spatial autocorrelation of the errors affects the estimates. We then estimate the SEM model by ML and GMM. The results are displayed in the two last columns of the Table 7. The value of l is significant and positive (l = 0.447) and no additional autoregressive spatial lag is detected. Some variations in the values of the parameters can be observed: once spatial autocorrelation is taken into account, the influence of the CBD is reduced and the influence of the proximity to a D-District is strengthened. Moreover, considering either the first model (colum 2) or the second one (colum 5) means that the influence of the D-Districts and of the CBD on the housing prices may be different. If we define $\hat{P}_1$ as the vector of the estimated prices with the first model and $\hat{P}_2$ as the vector of the estimated prices with the second model, we can evaluate the difference between the two estimated values. More precisely, we compute for each transaction the percentage of the difference between the estimated values produced by the first model and the second one : $\Delta\hat{P} = [\Delta\hat{p}_i]$ designs the corresponding vector[12].

Map 5: Estimated prices using SEM1 or SEM2



[12] For each transaction I, $\Delta\hat{p}_i = 100\dfrac{\hat{p}_{i1} - \hat{p}_{i2}}{\hat{p}_{i1}}$.

Looking at the Map 5, we observe that the transactions characterized by the largest difference ($|\Delta\hat{p}_i - m_{\Delta P}| > 2 s_{\Delta P}$ with $m_{\Delta P} = -0.094$ and $s_{\Delta P} = 4.08$) are located closer to the D-Districts or in the peripheral residential areas. In the first case, the prices are upper estimated whereas they are under estimated in the second case.

All these results illustrate the fact that ignoring both spatial dependence across the observed sale prices and the effect played by an housing urban policy leads to wrong evaluations. They also underline that the form takes by the negative influence of the D-Districts is not neutral, which results in different policy implications. In the first specification, one consider that the negative spatial externality produced by the D-District doesn't spread out: the price of an apartment located outside a D-District is not affected and we can consider that the housing market is segmented. On the contrary, the second hedonic function assumes a cross effect between housing sub-markets: to be located outside a D-District doesn't preserve from its depressive effect and it's better to be located far from a D-District than close to it. Moreover we also show that even if location is taken into account by the mean of accessibility and dummy variables, a spatial effect remains indicating that housing prices in each location are influenced by the housing prices in neighboring locations: local processes have to be added to the evaluation of housing prices.

5. CONCLUSION

In this paper, hedonic housing price functions take into account both spatial effects and neighborhood effects. Our results indicate that the inclusion of accessibility variables and neighborhood characteristics doesn't take all the spatial effects into account. Considering the fact that a neighborhood variable can be used to model the impact of the housing urban policies on the residential pattern of the COMADI, we have underline the role played by the social housing programs developed during the sixties and the seventies. If the negative influence of the D-Districts on the housing price spreads out towards the CBD, then the positive effect produced by a better accessibility to the Conservation Area is reduced.

Our analysis can be developed in at least three directions.

First, we haven't investigate the presence of spatial heterogeneity or the presence of outliers. It could be done by the use of Spatial Bayesian models as suggested by LeSage (1999).

Second, our results depend on the spatial structure described by the *W* weight matrix. We chose a 7 nearest neighbors *W* matrix since we thought that a distance-based *W* matrix took too many observations in downtown COMADI and not enough in the peripheral areas. On the contrary, choosing a fixed number of neighbors doesn't allow to capture the spatial variations of the sold apartment distribution. It appears that a density-based *W* matrix could be more appropriate.

Third, the presence of spatial externality could be further investigated considering a larger set of sub-markets if we think that other types of urban development policies have produced specific neighborhoods. In the same manner, we can take a land-use competition effect into account to discriminate between areas where multiple land uses are allowed from those where only one land-use is allowed (residential land use in fact in our case since we don't consider office transactions data)

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