Neighborhood Effects, Urban Public Policies and Housing Values
A Spatial Econometric Perspective

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ABSTRACT

Problems of spatial segregation are often associated with segmented housing submarkets where the social status and social capital of a neighborhood appear to be the main driving forces behind housing price formation. Urban regeneration policies aim to raise housing values in poor areas through the construction of new buildings with higher levels of housing services. Structural attributes, neighborhood characteristics, and accessibility variables are the determinants of housing values considered in hedonic models. In this paper, it is assumed that spatial effects in terms of spatial autocorrelation, spatial heterogeneity, and spatial externalities are additional variables worth considering for at least two reasons: (i) in econometrics, OLS estimation problems arise from the occurrence of spatial dependencies among housing values; (ii) in urban policy studies, spatial effects engender a global diffusion process extending beyond housing submarkets. The impact of social housing policies and urban regeneration policies may permeate outside the areas where they are implemented. Our case study is of the urban area of Dijon (France), where two types of urban policy have been implemented in the last three decades: social housing projects in some suburban areas, and a regeneration plan for the old inner-city. Spatial effects are introduced in the hedonic model and a spatial error model is estimated, revealing a positive and significant global spatial effect combined with the usual influence of accessibility to the CBD. We also show the negative influence of location in social housing districts and the spatial diffusion effect they exert on neighboring districts.

KEYWORDS

Deprived districts, hedonic model, housing price, neighborhood effects, spatial econometrics, urban policies

JEL Classification

C120, C520, R140, R210

1. INTRODUCTION

Urban policy makers are often confronted with problems of urban segregation and exclusion, obsolescence of older areas, and social marginality in inner-city areas, challenging them to find appropriate levers for urban regeneration policies (Adair et al., 1999). The question of spatial inequalities is complex, with disadvantaged areas exhibiting certain characteristics—low-income families, high unemployment, non-white residents, immigrant and transient populations, inadequate labor markets offering low-paid jobs, poor infrastructures, old and damaged buildings, a shortage of stores and public facilities, poor-quality environmental amenities—and rich areas their opposites. As a result, the social and economic characteristics of urban areas are closely interlinked and the attributes of neighborhoods and their residents are closely correlated. From a sociological standpoint, the *neighborhood effect* (Wilson, 1987) has proved useful when documenting the stigma attached to poor urban districts but problems have arisen when analyzing how neighborhood effects operate: empirical studies disagree about what is cause and what effect when it comes to neighborhood attributes and individual behaviors, i.e. they fail to go beyond the correlation between them (Bauder, 2002). In addition, the net social benefits for a city implied by a spatial redistribution of the poor (say through the Moving To Opportunity Program) is difficult to evaluate properly, as shown by Galster (2002).

Urban regeneration policies try to reverse the processes of economic, social, and material decline in deprived areas. In France, as elsewhere, redevelopment housing programs aim to improve the quality of life in poorer neighborhoods, to attract new residents, and to encourage poorer households to move to richer areas. Benefits from "social mixity" in the neighborhoods and positive effects of social and economic spillovers toward other neighborhoods are expected.

By considering residential patterns and urban policies in French cities, in this paper we aim to show that spatial analysis of housing values helps clarify the debate about urban regeneration policies. Four aspects are involved.

First, housing policies act on the characteristics of the areas where they are implemented. The impacts of public housing projects on property values have received little attention in the literature although negative or positive effects could be expected depending on whether the housing projects succeed or fail in creating positive amenities and externalities. In fact, different effects are generally expected, which could result in diametrically opposing amenities or externalities. On one side, public housing projects bring about urban renewal and so may have direct positive impacts on neighboring properties. As noted by Cummings and DiPasquale (1999) new dwellings are of higher quality than old dwellings and can raise the standing of the neighborhood and attract higher-income residents. The arrival of new residents could curtail existing bad neighborhood effects by introducing "social mixity" and dissuade higher-income populations from moving out. Against this, public housing projects allegedly increase congestion and noise, attract a majority of low-income families, thereby reinforcing the ill repute of the districts, and drive down housing values. Rabiega et al. (1984) showed a positive overall effect in the case of Portland, Oregon. By contrast Johnson and Ragas (1987), studying land values in the New Orleans CBD, explicitly introduced distance to a large housing project and expected a negative influence since such projects are widely perceived as sources of crime. However, they failed to prove this assumption owing to the lack of transactions in these areas and their surroundings. Rosenthal (2006), reviewing a panel of US metropolitan areas, shows that the presence of public housing has no significant effect on the neighborhood's economic status but that the Low-Income Housing Tax Credit

Program has a positive impact on the neighborhood's economic status in lower-income neighborhoods. Other ambiguous results are reported for US housing policies devised to increase quality of life and economic status in neighborhoods by promoting home ownership in redevelopment areas. In Philadelphia, where two Nehemiah developments were implemented in distressed neighborhoods, new homeowners do not really improve their quality of life. Nor is any evidence found of local benefits for adjacent real-estate prices and economic activities (Cumming et al., 2002). By contrast, a Nehemiah development in New York City does seem to have produced positive benefits on home prices in nearby areas (Ellen et al., 2001).

Second, research into neighborhood dynamics in terms of decline and renewal cycles has revealed that the age of housing goes a long way toward explaining spatial residential patterns, alongside local amenities or other forces found in the traditional urban model: e.g. commuting costs and housing demand. Using the concept of housing services rather than demand for housing units, since housing is a normal good, richer households are attracted by new buildings, i.e. high levels of housing services, whereas poor households locate in older buildings with lower levels of housing services. Extrapolating and considering a city neighborhood, if it is assumed that housing services deteriorate with the age of buildings, poor households will occupy old buildings vacated by rich households and when old buildings are demolished and replaced by new ones then rich households will return to the neighborhood. Economic theory of urban decline and renewal has collected interesting empirical evidence for US cities (Aaronson, 2001; Brueckner and Rosenthal, 2005; Rosenthal, 2006; Dye and McMillen, 2005). Applied to urban renewal policies, there is support for a gentrification process in downtown areas where old buildings are demolished and sites redeveloped with new and more expensive dwelling spaces.

The third aspect of the urban regeneration process is that housing values capitalize neighborhood characteristics. Local amenities (Brueckner et al., 1999), including natural heritage, heritage sites, and architectural characteristics of buildings, have a big effect on the residential location of Rich and Poor in metropolitan areas, specially the inner-city location of lower-income households in US cities, and the inner-city location of upper-income households in European cities. Cultural amenities act as a local force enhancing concentration in city centers (Baumont and Guillain, 2006). Racial segregation behaviors studied in some US cities (Cutler et al. 1999) may influence housing prices depending on a community's willingness to pay to keep its identity. Studying housing values in Baltimore, Dubin and Sung (1990) showed that the socio-economic status and racial composition of the neighborhood affect housing prices more than the quality of public services. Studying the influence of neighborhood externalities on the neighborhood's economic status on a panel of metropolitan areas in the US, Rosenthal (2006) reports a negative influence for race and for the population aged 15–29 but a positive influence for the presence of individuals with college degrees and of homeowners. The influence of income mixing remains mitigated depending on the level of the average income in the neighborhood: a positive impact is shown for middle-income communities but a negative one for the lowest and highest income categories. Social status and social capital of the neighborhood are strong determinants of neighborhood dynamics too through snowball effects: as the average income level falls, rich households move away; as the proportion of highly educated individuals increases in the neighborhood, more rich households move into the neighborhood.

Fourth, spatial effects characterize the distribution of housing values. From a technical perspective, spatial effects, in terms, say, of spatial autocorrelation and spatial heterogeneity, are known to engender estimation problems. Spatial autocorrelation yields inconsistent and inefficient OLS estimators and often occurs in conjunction with spatial heterogeneity in spatial processes (Anselin, 1988, 2001). Appropriate statistical and econometric tools are required to detect and process spatial effects. Empirically, modeling spatial effects in the housing price distribution helps capture similarities between real-estate locations and housing prices, describe spatial heterogeneity in the distribution of housing prices, and model spatial spillovers across transaction prices or neighborhoods. Finally, it appears that allowing for spatial effects provides a complementary perspective to the theoretical spatial pattern of the housing price gradient derived from traditional urban models by capturing local irregularities in housing prices. In the New Urban Economics tradition (Richardson, 1970) derived from the Alonso-Muth model (Alonso, 1964; Muth, 1969), the unit price of housing should fall with distance to the CBD. This general model has been extended to take account of local irregularities created, for example, by the development of a polycentric pattern: the housing price distribution exhibits an overall peak at the CBD location and local peaks at the location of subcenters (Papageorgiou and Mullaly, 1976), as has been empirically well documented (Baumont and Le Gallo, 2000). Other forms of empirical functional specifications have been developed to better capture the irregularities of the housing price distribution through cubic spline specification, for example. In addition, local irregularities have been handled by the use of explanatory variables indicating the existence of housing sub-markets (Basu and Thibodeau, 1998; Wilhelmsson, 2002), or spatial regimes (Páez et al., 2001), or by the use of recent estimation methods including non-parametric estimation methods, geographically (or locally) weighted regressions, or moving window approaches (e.g. Fotheringham et al., 1998; McMillen, 1996, 2004; McMillen and McDonald, 2004; Páez, 2003, 2007).

In this paper, we address the question of local irregularities implied by public housing policies and urban regeneration policies using spatial statistics and spatial econometrics. We focus on two types of urban policies implemented in French cities in the 1960s and 1970s: one related to a Conservation Area Plan in the core of the central city, and the other to social housing programs in peripheral districts. Positive or negative neighborhood effects observed 30 years later may have been caused by those policies. We show in the paper that taking account of spatial effects in hedonic housing price models allows the impact of such local irregularities to be estimated.

Our case study is a medium-sized French urban area: the *Communauté de l'Agglomération Dijonnaise,* abbreviated to COMADI, where two types of urban policy have produced areas with specific neighborhood attributes. Specifically, we are interested in three topics: 1/ studying the spatial characteristics of the distribution of housing prices in the COMADI, 2/ modeling spatial effects in the hedonic housing price function using spatial econometric specifications, and 3/ estimating the implicit prices of neighborhood and accessibility variables with regard to the spatial residential pattern produced by the different urban development policies: social housing programs and deprived districts in peripheral districts as opposed to urban regeneration policies and rich districts in downtown Dijon.

The paper is organized as follows. The next section describes the data, the urban policies, and residential patterns in the COMADI. In the third section, spatial effects in housing value patterns are documented and local irregularities are emphasized using exploratory spatial data analysis. Clusters of low housing unit-price values are detected in the deprived districts while clusters of high housing unit prices tend to be centrally located. Section 4 is a spatial econometric analysis of hedonic housing price functions including housing attributes, neighborhood characteristics, and accessibility variables. It is shown that neighborhood effects are associated with urban policies and that deprived districts display a significant negative neighborhood effect on housing prices, which moreover permeates to surrounding areas. In addition, the presence of spatial autocorrelation is detected and a spatial error model is estimated showing a global spatial diffusion process affecting housing values in the COMADI. The paper concludes with a summary of key findings.

2. Residential patterns in the COMADI

The data used in our study are described in the following sub-section. We then present the major urban development policies implemented by the COMADI in the last 40 years and show that they have produced two specific types of area: the Conservation Area and the Deprived Districts.

2.1. Housing data and explanatory variables

Our study focuses on a medium-sized urban area known as the COMADI (*Communauté de l'Agglomération Dijonnaise*), in Burgundy (France). It is a grouping of 16 local councils covering the city of Dijon, which is the regional capital of Burgundy, and its suburbs (Map 1).

Map 1: The 114 IRIS of the COMADI

With its 250 000 inhabitants, the COMADI may be considered as the economic core of the Metropolitan Area (MA) of Dijon, which, in 1999, was composed of 214 adjacent local council areas for a total area of 561 156 acres and 327 000 inhabitants. The COMADI accounts for 73% of the population of the MA, 86% of MA employment, and more than 90% of tertiary sector jobs. The COMADI is the most intensely urbanized part of the Metropolitan Area with more than 76% of the housing, the concentration being greater for apartments (97.2%) than for single-family homes (50%). Accordingly, if a household prefers to live in an apartment, it simultaneously chooses to live in the COMADI: location preferences express the quality of the neighborhood and accessibility characteristics of each location compared to other locations within the COMADI. By contrast, if a household prefers to live in a single-family home, it may choose to live inside or outside the COMADI, in which case location preferences express the quality of the neighborhood and accessibility characteristics of each location compared to other locations within and outside the COMADI. This being the case, restricting our study to the COMADI area while attempting to detect whether spatial effects influence housing prices or not would introduce bias. In addition, we know that the single-family home market and the apartment market are characterized by specific attributes. Hence the homogeneity of the sample is maintained by focusing on apartments alone.

Housing values are studied here using transaction data for apartments sold in the COMADI in 1999. Housing data are extracted from the *"Marché Immobilier des Notaires"* records supplied by the *"Chambre Départementale des Notaires de Côte d'Or"*. Since we focus exclusively on properties sold, our estimated results cannot be applied to the entire distribution of apartment values in the COMADI without selection bias (LeSage and Pace, 2004). The selection bias results from the possibility that transactions may be confined to apartments with specific characteristics (Tse, 2002). In fact, there are about 29 000 houses and 73 500 apartments in the COMADI and total housing transactions in 1999 concerned 3% of them. We ignore house transactions for the reason stated above and concentrate exclusively on transactions of apartments for which the transaction price and certain essential structural attributes are available. Our sample contains 1520 transactions.

Hedonic models are widely used for estimating housing values on the basis of a large set of attributes generally grouped into three subsets: 1/ *structural variables* describing the physical characteristics of housing, 2/ *neighborhood or environmental variables* depicting the quality of amenities and the economic and social characteristics of the neighborhood, and 3/ *accessibility variables* including distances to major places of employment, to major amenities (leisure, shopping and public facilities, outstanding sites, etc.), and to road infrastructures and transport access points (train stations, subway stations, major streets, highways, airports, etc.).

Considering the available variables in the data set, the characteristics of properties are captured by their size (floor space in square meters), number of rooms, number of bathrooms, period of construction (grouped into seven construction cycles), and the presence of a loft, cellar, balcony, or terrace. The exact location of the apartment is given by its geographical coordinates which allows us to associate each apartment with a neighborhood.

The neighborhood is assimilated to the finest geographical statistical unit available at the city level, which is known as *IRIS (Ilôt Regroupé pour l'Information Statistique)*. An IRIS is a cluster of contiguous blocks based on population size (at least 2000 people), or on economic size. The COMADI is divided into 114 IRISes (see Map 1 for a picture of the IRIS scale) each designating a neighborhood. In 1999, at least one transaction occurred in 92 of them. IRIS data are provided by the *Direction Régionale de l'INSEE* (French national statistics institute). A large set of neighborhood variables are available at the IRIS scale describing their socio-economic characteristics: population density, unemployment rate, professional group composition, population educational levels, immigrants. Census data on housing conditions such as vacancy rate and building types are also available at the IRIS scale. Other variables measuring the quality of neighborhood amenities are generally included in housing studies: distance to the nearest park, distance to an elementary or primary school, to a junior high school, and distance to a shopping center. The COMADI has 27 shopping centers, 98 elementary and primary schools, 29 junior high schools and 34 parks. Since the COMADI area is small (42 600 acres), it is safe to assume that all housing is located close to such amenities and public facilities and that including these distance variables would at best not be very significant and at worst would engender a multicollinearity problem (Heikkila, 1988).

As regards accessibility variables, which express the way proximity to some specific characteristics of the urban space may affect the spatial distribution of housing prices, we naturally consider the distance to the main economic center (CBD), which is centrally located in the COMADI. Since subcenters have emerged in the COMADI in recent decades, we need to test their local influence on housing prices and so we use the inverse distance to the nearest employment subcenter. To avoid multicollinearity problems, accessibility to the train station is not considered since it is centrally located in the CBD. Neither is accessibility to highways considered since the study relates to housing values in the urban area bounded by those highways. Another reason to ignore accessibility to major infrastructure networks is that the COMADI area is small and that only a small proportion (11.6%) of the population living in the COMADI works outside it: commuting outside the COMADI is not time consuming.

Finally, in the context of urban regeneration policies, we consider two additional neighborhood variables associated with urban development policies: location in a deprived district or in the Conservation Area. To test whether the impact of urban policies on housing prices is confined to their targeted areas or whether spatial diffusion effects arise, we introduce distance to the nearest Deprived District. Proximity to the Conservation Area is captured by distance to the CBD since the Conservation Area lies within the CBD (see Map 2). Table 1 reports the variables used in our various analysis (statistical analysis of neighborhood quality, statistical description of districts targeted by urban development policies, exploratory spatial data analysis of housing price distribution and estimation of hedonic models).

Table 1: Variables – Summary Statistics

On average, an apartment in the COMADI sells for €64 575 but the deviation from the mean is relatively high (σ = 35 959). The smallest apartment has a floor space of 11 m^2 and the largest of 306 m^2. The average unit price is €1042 per m^2 (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 fewer than 10 transactions and 31 sub-markets have more than 20 transactions. The oldest sub-markets correspond to IRISes that are centrally located in the COMADI and they naturally have more apartment transactions than the peripheral sub-markets where there are more single-family houses than apartments. Some 32% of housing transactions involve apartments built between 1949 and 1969 as against 29% for 1970–1980. New apartments (built after 1991) represent only 3% of the sample as opposed to 6% for the oldest apartments (built before 1850).

2.2. HOUSING AND URBAN DEVELOPMENT POLICIES IN THE COMADI

Since the early 1960s two types of urban development policy have structured the spatial residential pattern of the COMADI, giving it its main current features. In the 1960s and 1970s various planning programs, sustained by the economic growth and the demographic expansion that followed the Second World War, were carried out in which land-use zoning and gigantic proportions were the rule: residential districts on some sites, large industrial or commercial estates on other sites, and major public services and urban amenities on yet other sites. The urbanized areas doubled in 25 years and two major forms of urban sprawl covered peripheral districts. First, several social housing programs, characterized by high-rise blocks, were carried out in the districts of Fontaine d'Ouche and Les Grésilles located in the city of Dijon, in Talant (Belvédère district), Chenôve, and Quetigny. Second, the main industrial and commercial estates were developed in the North, in Chenôve, and in Quetigny. This was the beginning of sub-urbanization of the population and of the emergence of employment subcenters (see Map 2).

At the same time, the *Conservation and Improvement Area Plan*, instituted by the 1962 legislation known as the *loi Malraux*, was drawn up and implemented: 295 acres in downtown Dijon are covered by this plan and it is the largest such conservation area in France. This area named "Vieux Dijon" corresponds roughly to the medieval town, where the major administrative buildings are located (Dijon City Hall, COMADI Council, Regional Council, Prefecture), together with the cathedral and several churches, the covered market, and many old, architecturally interesting buildings. The conservation area is a mixed area characterized both by high population densities and high employment densities because the CBD is located there (see Map 2.).

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

The *Conservation and Improvement Plan* is aimed at "improving the quality of life in the core of Dijon" along three main lines.

1/ Conserving and renovating old buildings in keeping with their architectural characteristics and enhancing them by developing their surroundings.

2/ Improving housing in central areas by refurbishing old buildings (by means of OPAH: *Planned Housing Improvement Operations*) and by constructing new buildings in keeping with the spirit of the architectural heritage. More than 1200 old apartments have been refurbished and 500 new apartments have been built in the last 15 years.
3/ Developing the cultural and economic attractiveness of downtown Dijon and improving access through specific actions directed at solving street congestion problems. In the 1980s, the city council chose to restrict automobile traffic flows in the inner streets, to build five new parking lots on the edge of the conservation area and to develop public transportation. Many streets and public areas were converted into pedestrian areas and pedestrian shopping streets. Café terraces and sidewalks now replace open-air parking lots. The pedestrian area covers 70% of the conservation area. These various measures have helped to sustain the gentrification of downtown Dijon since the early 1960s.

The attractiveness of downtown Dijon contrasts with the poor social and economic conditions in the social housing districts developed over a 30-year period in the peripheral districts to cope with population growth. These districts, hereafter referred to as Deprived Districts (D-Districts) are mainly characterized by a lack of public facilities and shops, poor environmental quality, very dilapidated housing, a large immigrant population, a large proportion of low-income households, rapidly rising crime rates, etc. Since the beginning of the twenty-first century, the French government, the COMADI councils and the city council have been engaged in an extensive urban renewal policy (*Politique de la Ville*) devised to improve the social and economic status of the deprived districts (referred to under this policy as *Zones Urbaines Sensibles* or *Quartiers Politique de la Ville*). These deprived districts lie in one or more IRISes and correspond to the five Deprived Districts studied here.

Various characteristics of the D-Districts and of the Conservation Area can be highlighted using the set of neighborhood variables previously described and supplemented by census housing data available at the IRIS scale (Table 2).

Table 2. Summary statistics: Conservation Area and D-Districts

They display contrasting features. For example, the Conservation Area is characterized by a high percentage of residents in higher management and professional occupations (28.4% versus 15.8% for the COMADI, and less than 7% for the D-Districts), a low percentage of clerical workers (22% versus 31% for the COMADI, and more than 32% for the D-Districts) and manual workers (10% versus an average of more than 22% in the COMADI and between 29% and 44% for the D-Districts). In Dijon center too, we find a very low proportion of immigrants (4.7% versus more than 8.7% and up to 17.6% in the D-Districts) and the population is highly qualified with more than 2.9 times as many university graduates as people with no qualifications (the average is 1.27 in the COMADI and less than 0.37 in the D-Districts). For housing, the Conservation Area has a high proportion of old buildings and apartments (82% of the apartments were built before 1949), a high vacancy rate (13.4%, which is twice the average in the COMADI and higher than in the D-Districts except for Les Grésilles) but a very low percentage of social housing (5.3% versus 22% for the COMADI, more than 51% and up to 78% for the D-Districts). Economic development is very contrasted too: the Conservation Area concentrates a large proportion of the total employment of the COMADI (more than 11%) whereas the D-Districts are poorly developed: the Conservation Area is a mixed area with a big local employment market but D-Districts are residential areas and do not provide any jobs at all.

However, both types of area have similar characteristics: high population densities (50 inhabitants per acre on average as against fewer than 6 inhabitants per acre for the COMADI), similar percentages of residents in intermediate occupations (lower on average than for the COMADI), and similar rates of unemployment (10% on average except for the D-District in Chenôve which is higher: 19%).

It appears that the neighborhood quality of the Conservation Area and the Deprived Districts is well described by specific combinations of neighborhood variables, raising a potential problem of multicollinearity to be taken into account in the estimations. In particular, the correlation analysis conducted for the neighborhood variables and on the set of COMADI submarkets[1] shows that some variables are closely correlated with the others: the percentage of residents in higher management and professional occupations, the percentage of residents in manual occupations, the level of education. For the urban development districts only (Conservation Area and D-Districts), the percentage of immigrants is correlated with the D-Districts, the building period “1948-1969” is correlated with the D-Districts, and the building period “before 1848” is correlated with the Conservation Area. Finally, the population density is correlated with both types of urban development districts.

These preliminary results highlight the close association between the social status and the economic status of a neighborhood, which has been evidenced in US cities of all sizes too. They illustrate the spatial roots of past urban development policies too and how difficult it is to implement urban renewal policies. Some complementary and far-reaching considerations of spatial effects associated with urban development policies in the COMADI are now discussed.

3. SPATIAL EFFECTS ON HOUSING PRICES AND URBAN DEVELOPMENT POLICIES

The spatial distribution of housing values and hedonic models of housing prices are affected by spatial effects, and we first recall the major reasons why. Spatial effects in the housing unit price distribution are then analyzed at the global scale and at a local scale.

3.1. SPATIAL EFFECTS ON HOUSING PRICES

Spatial autocorrelation and spatial heterogeneity characterize housing values and hedonic models for at least three major reasons.

– Housing is a durable good in a fixed location. Accordingly, properties within the same neighborhood capitalize shared locational amenities, have similar access to labor markets and public facilities, and are affected by the same spatial externalities. In addition, houses and buildings within a neighborhood were often built at the same time and tend to have similar structural characteristics. As a result, housing prices may be spatially autocorrelated.

– Spatial heterogeneity may occur if, for example, coefficients are different depending either on distance from the CBD (in an isotropic or an anisotropic space), or on a spatial regime structure, or on other forms of spatial segmentation. In the latter case, spatial segmentation may be intra-urban, based on housing characteristics (old or recent buildings) or population characteristics (household income, race, unemployment rate, etc.). 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 another district can be interpreted as heterogeneity among prices or as a spatial autocorrelation process yielding clusters of similar values. Moreover, spatial autocorrelation in residuals may result from spatial heterogeneity that is incorrectly modeled in the hedonic price equation.

– Many neighborhood and accessibility variables are difficult to measure because they are unobservable (like the quality of public facilities), or complex (the crime rate or prevalence of 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 outstanding sites, etc.) and the way accessibility to them can be measured. In addition, such variables are rarely available in data bases. Even if relevant and reliable data are available, the problem of identifying the relevant neighborhood boundaries may remain (Dubin, 1992; Basu and Thibodeau, 1998). Selecting the best set of explanatory variables and the correct model specification is also difficult (Sheppard, 1999). And again, the residuals produced by hedonic models of housing prices may be correlated owing to measurement errors on the variables, omitted variables, or other forms of hedonic model misspecifications (McMillen, 2003).

Although hedonic housing price models include accessibility or neighborhood variables, which tend to introduce spatial effects into the modeling and estimating processes, only a few empirical studies have applied appropriate econometric techniques to detect and take account of such spatial effects. In other words, allowing for spatial effects means that even when neighborhood and accessibility variables are included in housing value functions as explanatory variables, spatial dependency may persist. In addition, taking account of spatial autocorrelation improves the estimates and the forecasts on real estate markets, is a substitute for omitted variables, or makes it possible to capture spillover effects and spatial externalities (e.g. Anselin, 2003; Anselin and Le Gallo, 2006; Beron et al., 2004; Can and Megboluge, 1997; Dubin, 1992, 1998; Gilley et al., 2001; Irwin, 2002; Irwin and Bockstael, 2001, 2002, 2004; LeSage, 1996, 1998; LeSage and Pace, 2004; Pace and Gilley, 1997; Pace et al., 1998; Paez, 2003, Paez et al. 2001; Tse, 2002).

Evidence of spatial effects in the COMADI housing price distribution is analyzed by means of Exploratory Spatial Data Analysis (ESDA). We show that the Conservation Area on one hand and the Deprived Districts on the other exhibit specific patterns of spatial effects.

3.2. EXPLORATORY SPATIAL DATA ANALYSIS OF THE UNIT PRICE DISTRIBUTION

When studying spatial dependency in housing price distribution and in hedonic housing price equations, it is necessary to incorporate a spatial structure, the familiar *W* weight matrix, which quantifies how an observation at one location is connected to other observations at neighboring locations: each apartment *i* is connected to a set of neighboring apartments *j* according to an exogenously defined spatial pattern. The elements w_{ij} on the diagonal are set to zero whereas the elements w_{ij} indicate the way unit i is spatially connected to 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 to one.

Several types of spatial structure may be used to find the best fit for the spatial data characteristics: contiguity through a common boundary, nearest neighbors, distance-based functions. In our case, two characteristics have to be considered. On one side, the price of an apartment is more influenced by the prices of the closest apartments, making us lean toward a distance threshold *W* matrix.

The general form of a distance threshold weight matrix $W(\bar{d})$ is:

$$\begin{cases} w_{ij}^{*}(\bar{d}) = 0 & if \quad i = j, \quad \forall \bar{d} \\ w_{ij}^{*}(\bar{d}) = 1 & if \quad d_{ij} \leq \bar{d} \\ w_{ij}^{*}(\bar{d}) = 0 & if \quad d_{ij} > \bar{d} \end{cases} \qquad \text{and} \qquad w_{ij}(\bar{d}) = w_{ij}^{*}(\bar{d}) / \sum_{j} w_{ij}^{*}(\bar{d})$$

where $w_{ij}(\bar{d})$ is an element of the standardized weight matrix and $\bar{d}$ is a critical cut-off distance beyond which neighboring transactions have no influence.

The occurrence of isolated transactions in the sample may be incompatible with a short cut-off distance. For example, in our case, with a cut-off distance of 100 m, 267 observations have no connections while one observation has 20 neighbors. If the cut-off distance is 250 m, only 33 observations have no connections while 611 observations have at least 20 neighbors. On the other hand, when the transactions distribution is spatially diversified with large sets of transactions in central areas and small sets of transactions in peripheral areas, using a *k* nearest-neighbors *W* matrix allows us to consider for each transaction the same number of neighboring transactions.

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

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

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 such that each unit *i* has exactly *k* neighbors. Although the *k* nearest neighbors matrix offsets the variation of the set of neighbors implied by the distance threshold matrix, it appears somewhat artificial for large values of $d_i(k)$: in that case, it means that some housing prices are influenced by distant transactions, which could be problematic.

One way to combine the two spatial structures is to build a *k* nearest-neighbors *W* matrix with decreasing weights as distance between observations increases. Using the inverse distance function as a decreasing function, the general form of the $W_k(d_{ij})$ matrix is:

$$\begin{cases} w_{ij}^{*} = 0 & \text{if} \quad i = j \\ w_{ij}^{*} = \dfrac{1}{d_{ij}} & \text{if} \quad d_{ij} \leq d_i(k) \\ w_{ij}^{*} = 0 & \text{if} \quad d_{ij} > d_i(k) \end{cases} \qquad \text{and} \qquad w_{ij} = w_{ij}^{*} / \sum_{j} w_{ij}^{*}$$

In order to check the robustness of our results, we consider three spatial matrices: a 7 nearest neighbors binary matrix W(7), a cut-off distance $\bar{d}$ =250 m for the binary matrix $W(\bar{d})$ and the weighted $W_7(d_{ij})$ matrix.[2]

For the distribution of housing unit prices (measured in € before tax), two types of spatial association were tested: global spatial autocorrelation and local spatial association. Global spatial autocorrelation, which is usually based on Moran's *I* statistic (Table 3)[3], shows that housing unit prices are positively spatially autocorrelated at the p = 0.0001 significance level[4]. As expected, the results indicate that similar housing unit prices tend to be spatially clustered in the COMADI.

Table 3: Moran's I statistics for housing unit price distribution in 1999

Moran's I is a global measure and does not permit us to appreciate local patterns of spatial association, i.e. to detect whether transactions in areas targeted by urban development policies exhibit specific spatial associations in terms of clusters of high (resp. low) unit prices in the Conservation Area (resp. in the Deprived Districts). 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 atypical spatial associations compared to the global pattern of positive spatial autocorrelation. Detailed analysis of the location of such atypical clusters may reveal spatial cleavage induced by urban policies.

Local spatial associations were examined by means of Moran scatterplots and Local Indicators of Spatial Associations LISA (Anselin, 1995, 1996). In a Moran scatterplot, the values of a spatial lag variable *Wz* are plotted against the values of the variable *z.* The scatterplot displays four types of local spatial association between an observation and its neighbors, each being localized in a quadrant of the scatterplot: quadrant HH refers to an observation with a high[5] value surrounded by observations with high values, quadrant LH refers to an observation with low value surrounded by observations 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:

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

where x_i is the unit price of the observation *i*; *n* = 1520; μ is the mean of the observations and where the summation over *j* is such that only the unit prices of the neighboring apartments of *i*, defined by the spatial *W* matrix, are included.

A positive value I_i indicates spatial clustering of similar values (high or low) between an apartment and its neighbors whereas a negative value indicates spatial clustering of dissimilar values. Due to the occurrence 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. 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 allowing for the number of multiple comparisons have to be used. 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 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 binary and the weighted 7 nearest neighbors matrices, the maximum number of common neighbors is 7, so the pseudo significance level is p = 0.00714. In the case of a threshold distance we use the maximum number of connections which is 60 when $\overline{d}$ = 250 m and the pseudo significance level is 0.0009. Finally, a Moran significance map combines the information in a Moran scatterplot and the significance of LISA by showing the apartments with significant LISA values and color-coding the quadrants in the Moran scatterplot to which these apartments belong.

Applying these tools to the unit price distribution yielded the following results.

First (Table 4), it appears that almost 70% of the unit prices are characterized by positive local spatial associations (HH or LL).

Table 4: Spatial association patterns (LISA) of housing prices

Using Bonferroni's correction, more than 80% of the significant LISAs are of HH or LL types showing evidence of several pockets either of low or of high transaction prices in the COMADI (see Table 5). Second, almost 90% of the LL spatial associations are located in D-Districts and such a local spatial association is never observed in the Conservation Area (Map 3 and Map 4 display the points for the 7 nearest neighbors binary matrix). No local association of HH type is observed in a D-District and more than 50% of the HH associations are located in the Conservation Area.

Table 5: Significant spatial association patterns (LISA) in urban development areas

Map 3: Moran significance map for HH and HL spatial association

Map 4: Moran significance map for LL and LH spatial association

Some apartments in the Core of Dijon are of the LH type. Since 67% of apartments sold there were built before 1947, this may reflect their poor state of repair and need of refurbishment and may argue in favor of continuing the measures for the gentrification of downtown Dijon. We also note that some local spatial associations of the HH type also characterize transactions in areas outside the Conservation Area.

Finally, the results highlight the impact of spatial effects on the housing price distribution within the COMADI in two ways. First, housing unit prices are positively spatially autocorrelated, indicating 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 closely linked to the D-Districts whereas the role played by the Conservation Area appears positive. Urban development policies seem to have structured the spatial pattern of housing price in two distinct ways. These points can be investigated by estimating hedonic housing price functions.

4. SPATIAL MODELLING OF HEDONIC HOUSING PRICE FUNCTIONS

4.1. ECONOMETRIC SPECIFICATIONS

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

$$P = A\alpha + N\beta + D\gamma + \varepsilon \qquad \varepsilon \sim \mathbf{N}(0, \sigma^2 I) \qquad [2]$$

where P is the $(n \times 1)$ vector of housing prices, A is a $(n \times m)$ matrix of structural attributes of the apartment (plus the constant), N is a $(n \times t)$ matrix of neighborhood characteristics, D is a $(n \times q)$ matrix of accessibility variables, α, β and γ are, respectively, m, t and q length vectors of unknown parameters to be estimated, and ε is a random error vector with the usual properties.

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:

$$P = \rho WP + A\alpha + N\beta + D\gamma + \varepsilon \qquad \varepsilon \sim \mathbf{N}(0, \sigma^2 I) \qquad [3]$$

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

The spatial error model is:

$$P = A\alpha + N\beta + D\gamma + \varepsilon \quad \text{with} \quad \varepsilon = \lambda W\varepsilon + u \quad \text{and} \quad u \sim \mathbf{N}(0, \sigma^2 I) \qquad [4]$$

where λ 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 WP and reflects the point 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 stem from various forms of misspecification (omitted variables, lack of adequate neighborhood measures, etc.).

Ignoring spatial dependence when it is present produces OLS estimators that are 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 by the Maximum Likelihood (ML) method. Since our aim is to deal with the general impact of spatial dependence in estimating 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[6]: spatial autocorrelation of errors or endogenous spatial lag.

Where estimates for ρ or λ are significant, spatial autocorrelation may be interpreted as a spatial externality at work in the housing price formation whose intensity depends on the estimated values of the parameters and whose spatial scale depends on the spatial connection pattern defined in the W matrix.

4.2. VARIABLES AND RESEARCH ISSUES

Taking into account structural attributes, neighborhood attributes, and accessibility variables in hedonic housing price models permits us to estimate consumers' willingness to pay for housing attributes, neighborhood quality, and accessibility and to clarify residential behaviors in urban space. More interesting is the choice of appropriate variables for investigating two major theoretical fields in urban economics concerning the analysis of changes in economic and residential patterns—the emergence of subcenters and the gentrification process.

First, the emergence of secondary employment centers can be questioned. In a monocentric urban area we expect the unit price of housing to fall with distance from the CBD whereas in a polycentric urban space we expect the unit price distribution to exhibit a global peak near the CBD and local peaks near secondary employment centers. More generally it is expected that the distinction between CBD and suburban location weakens (Brueckner and Rosenthal, 2005). Moreover, it is assumed that the CBD exerts an overall influence on housing price levels whereas employment subcenters compete with each other and exert just 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 (e.g. Sivitanidou, 1996). Using Giuliano and Small's (1991) identification method, Baumont et al. (2002) identified three employment subcenters: one located in the North, one in the South and a third in the business district of Quetigny. Using spatial econometric procedures, Baumont et al. (2004) showed that these subcenters did not influence the population density distribution in the COMADI. However, it is interesting to study whether housing value, which is a more flexible variable than intra-urban population density, is influenced both by the distance to the CBD and by the distance to these employment subcenters.

Second, many urban renewal policies are regularly implemented and have been recently strongly reactivated through gentrification processes in many cities, but only a few empirical studies have investigated this issue directly, i.e. to evaluate the impact of housing policies in urban areas. It may be interesting, then, to see whether the different urban development policies have produced different spatial externalities according to the type of areas (Conservation Area or D-District) in which the apartments are located. We include the D-District, MinD-D and C-AREA variables in the hedonic functions to address this issue. Instead of the D-District dummy variable, the MinD-D variable captures the influence of being located close to a D-District. Symmetrically, the proximity to the Conservation Area is captured directly by the distance to the CBD since, as in many French cities, the CBD is located in the historical district where *the Conservation and Improvement Area Plan* could be applied (see Map 2).

Finally, the sets of explanatory variables we included in the three matrices of housing attributes [A], neighborhood characteristics [N], and accessibility variables [D] are:

A = [SURF BATH YEAR5013 YEAR1447 YEAR7080 AFT1980 TERBAL CELLOFT]

N = [Intermediate Clerical DensPop Vacant High-Educ Foreign D-District Cons-AREA]

D = [Dist-CBD INV-MinSubcenter MinD-District]

Recall that some socio-occupational groups are ignored so as to avoid multicollinearity problems: the percentage of residents in higher management and professional occupations, and the percentage in manual occupations are closely correlated with other groups and with the neighborhood status. Two building periods are omitted too: that before 1850 because all old apartments are located in the Conservation Area and that between 1948 and 1969, which corresponds to the main building periods in social housing districts.

4.3 ECONOMETRIC RESULTS

Following the hedonic modeling literature, we use the log-transformation on the dependent variable and on the explanatory variables[7] 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): $100 \times \left[\exp(\hat{d}) - 1\right]$.

Taking the log transformation of the sale price (L-PRICE), the results of OLS estimation of the hedonic models are shown in Table 6. Four models have been successively estimated in order to analyze the impacts of urban policies on housing values, the structural attributes always being considered: the core model (Model 1) with the variables for accessibility to the CBD and deprived districts, supplemented in Model 2 with the variables associated with urban policies. The last two models allow us to analyze the impact of the neighborhood status on housing values. In Model 3, we aim to estimate the impact of social capital measured by the presence of educated individuals. We try to check the impact of social status too as described by the percentage of foreigners, the population density, and the percentage of vacant housing. In Model 4, we explicitly consider the neighborhood variables associated with urban policies as in Model 2, which prevents us from including the same social indicators owing to potential multicollinearity problems. We choose instead two socio-occupational groups whose location behaviors are less predictable—intermediate occupations and clerical occupations—and we include population density and the percentage of vacant apartments.

Table 6: OLS estimates for the hedonic housing price function

All models account for at least 79% of the variation in price and if one were to assume no spatial autocorrelation problem, the results of the OLS estimation would suggest the following interpretations. Price rises at a slightly decreasing rate with floor space since the elasticity is 0.93 and the unit price is lower for big apartments than for small ones. Looking at the structural attributes[8], the impact of the number of bathrooms is positive and significant (an extra bathroom raises the price by about 12% on average), the presence of a terrace or a balcony raises the price by about 6% and the presence of a cellar or loft raises the price by about 2.5% For an apartment, having been built in the period 1850–1913 lowers the price (by about 7.5%). On the contrary, a construction date between 1970 and 1980 (resp. after 1980) raises the price by 8.3% (resp. 28%). The impact of the building period “1914–1947” is negative but not significant at 5%, except in the third model: the impact falls off by about 5%.

The CBD distance gradient is significant and negative and, other things being equal, price decreases at a decreasing rate with distance to the primary labor market of the urban area as predicted by urban models. The magnitude of the decreasing gradient depends on the model: it is larger when we consider the core model with no neighborhood variables (-0.065%) but it is smaller in Model 3 (-0.031) but remains important. On the contrary, as indicated by the estimates in Model 2, accessibility to a secondary employment center is not significant: the emergence of peripheral subcenters in the urban area has no influence on the spatial distribution of housing prices. This suggests that the spatial pattern is strongly defined by the primary CBD and that new centers appear more in a fixed residential pattern than in a modifiable one. Within the COMADI, the influence of subcenters is probably dominated by the power of the CBD: the housing price distribution is not influenced by subcenters like residential density population is (Baumont et al., 2004). In fact, our result is consistent with other studies which also show that the influence of subcenters on residential property values is rarely significant even in very large metropolitan urban areas: "Although jobs are increasingly likely to be located in subcenters, workers do not appear to be bidding more for homes closer to their workplaces". (McMillen 2004).

On our assumption, proximity to housing projects has a negative impact on housing prices: location well away from a D-District invariably increases the price of the apartment since the value increases with distance to the nearest D-District even if this benefit is only slight. Some complementary insights on the impact of economic and social status of the neighborhood are drawn from Model 2. Being located in the Conservation Area brings no significant influence compared to other areas provided it is not a deprived district. In such districts prices are some 18.6% lower. Combined with the fact that D-Districts are located on average 3.5 km from the CBD, location in a D-District strongly depreciates the value of an apartment in the COMADI. In other words, the negative influence of the D-District extends beyond the rundown area, and being located far from a D-district prevents the depreciation of housing values.

As for other neighborhood attributes (Model 3), if the education level increases by 1%, the price will increase by 0.08%. This result illustrates the significant impact of the social capital on housing price as highlighted in other studies too (Rosenthal, 2006). There being more educated individuals in the conservation area contributes to higher housing values in the old renovated inner city than in suburban social districts. The impact of social status is evaluated in our study by the percentage of foreigners living in the districts but the impact, although of the expected negative sign, is not significant. Another way to measure the social status of the neighborhood is by its social group composition (Model 4). While the percentage of intermediate occupations has a significant and positive influence on housing values (elasticity is 0.14%), the impact of the clerical occupations group is negative with an elasticity of -0.11%. The proportion of residents in intermediate occupations in D-Districts is in some cases as large as in the Conservation Area. For future urban regeneration policies, this result supports the investment in new buildings to attract more people in intermediate occupations and so foster the gentrification process. The rate of vacant housing is not significant in either model 3 nor 4. The impact of population density is either not significant (Model 3) or positively significant (Model 4) with an elasticity of 0.02. Both positive and negative impacts on social interactions may result from density: high density levels increase social interactions but limit them through congestion or other nuisances. The net positive impact captured in Model 4 speaks in favor of net positive impacts derived from density once the negative impact of being located in a deprived district has been controlled for.

OLS estimates have to be looked at carefully because of potential spatial dependence effects. Looking at the five spatial tests, the same diagnostics are found for all the models[9]. It is worth noting that *Moran's I* test does not reject the null hypothesis of the absence of spatial autocorrelation. The Lagrange Multiplier tests, *LMERR*, *LMLAG* and their robust versions *R-LMERR* and *R-LMLAG* (Anselin, 1988; Anselin et al., 1996) were performed to discriminate between the two forms of spatial autocorrelation: spatial autocorrelation of error or endogenous spatial lag. Applying the decision rule proposed by Anselin and Florax (1995) [10], 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 the observations are spatially interdependent. Statistical inference based on OLS estimators is unreliable.

The estimates of the SEM model by ML and by the iterated General Method of Moments (GMM)[11] are shown in Table 7. Model 5 is the spatial error specification of Model 3 and Model 6 is the spatial error specification of Model 4 without the conservation area dummy variable which was not significant at all. It appears that the spatial econometric estimates confirm the effects of the significant explanatory variables and that in addition a significant positive spatial autocorrelation of the errors is found ($\hat{\lambda} = 0.21$ for the model 5 and 0.23 for the model 6). This can be interpreted as a positive spatial diffusion effect among housing prices. The spatial models perform better in terms of information criteria than the non spatial models previously estimated.

Table 7: Spatial Error Model estimates for the hedonic housing price function

Two major implications for urban public policies can be drawn regarding both the spatial dimension of the housing market and the capitalization of neighborhood attributes by housing values. If no spillover effects are assumed, then we can consider that housing markets are segmented: the housing value in a particular area is not influenced by the values of properties in other areas after having controlled for structural and neighborhood attributes. Testing for spatial dependence in regression can then be used to investigate the spatial segmentation market hypothesis according to the exogenous spatial pattern defined in the spatial weight matrix. The estimated value of the spatial parameter in the SEM model indicates a spatial diffusion process between housing values. One has to consider that spatial externalities produced in a specific location can extend beyond it and that housing markets are not spatially segmented. Leaving housing conditions and locational amenities of a district to deteriorate is bad for the district and for neighboring districts. On the contrary, improving housing conditions and locational amenities in a district has a positive influence on the housing values of neighboring districts.

In addition, the spatial diffusion of a random shock in one property can be studied by means of the Spatial Error Model [4] rewritten in the form:

Since $\varepsilon = \lambda W\varepsilon + u$ then $\varepsilon = (I - \lambda W)^{-1}u$ and $P = A\alpha + N\beta + D\gamma + (I - \lambda W)^{-1}u$ [5]

It indicates that a random shock in a specific property is propagated to all the properties of the sample through the spatial inverse transformation $(I - \lambda W)^{-1}$, even if the property has a limited number of neighbors: the spatial process is then global, meaning that each housing value is a potential emitting source of change for the entire distribution of housing values as it is a reception point of any change in housing values of the distribution. The impacts of reception and emission associated with random shocks depend on the housing value distribution and on the spatial pattern described by the spatial weight matrix. Considering the latter, i.e. geographically, it is easy to understand that these impacts decrease with distance and that a centrally located place is globally better than a peripheral location while the housing value distribution, i.e. the economic side of the analysis, may weaken or reinforce this core–periphery pattern[1]. In any case, urban renewal policies may have positive effects on various districts throughout the urban area and improve the potential performance of housing markets. Urban regeneration planners need, then, to support the construction of new buildings with a higher level of residential service to attract households who will bid more for a modern apartment. The positive impact expected in the targeted district will then permeate through the urban area, making the city more attractive.

Our study illustrates two types of contrasting urban policy developed over a 30-year period in the COMADI. In social housing areas, urban policies were merely mechanisms for achieving economic and physical regeneration rather than for integrating social regeneration and interactions within the urban system. Negative stereotypes of social housing areas have acted as a cumulative process of urban decay one can describe as a cultural model of poverty (Bauder, 2002; Rosenbaum et al., 2002), which was capitalized by the housing sub-markets. On the contrary, in the conservation area, where good economic conditions, a high level of public facilities, and many architectural potentialities co-exist, urban regeneration policies have been in step with market conditions and created a cumulative process of investment in this part of the urban area that may be described as a gentrification process (Helms, 2003). Within the same urban space, then, the geographical location of housing sub-markets appears to be a good substitute for their economic characteristics and plays an important role in household location decisions. Urban renewal policies implemented in the late 20th century have brought about such neighborhood effects in two ways: by improving the social mix in all areas and by improving living conditions in the deprived districts, which are considered as target areas for housing refurbishment, mixed land use, greater housing variety, and infrastructure improvements.

5. CONCLUSION

We have estimated hedonic housing price functions taking into account spatial effects, neighborhood attributes, and accessibility variables. Considering that neighborhood variables can be used to model the impact of urban housing policies on the residential pattern of the COMADI, we have underlined the role played by the social housing programs and conservation area plan developed over the last 30 years. In addition, spatial effects in terms of spatial autocorrelation or spatial heterogeneity could characterize housing markets and imply some spatial diffusion processes in the housing value distribution. Exploratory spatial data analysis has indicated that the unit price distribution exhibits global and positive spatial autocorrelation with significant local clusters of low unit prices located mainly in the deprived districts. Diagnostics for spatial autocorrelation in the OLS estimation of the hedonic housing price function having suggested a spatial dependence of the errors, we have estimated a spatial error model with the following results. The negative impact of the deprived districts is strong and extends beyond them. The spatial parameter is significant and positive, suggesting spatial dependencies between housing sub-markets and a global spatial diffusion process of a random shock to the entire housing price distribution. Since households attribute negative or positive images to areas within the urban space and attach importance to the place where they wish to live, the challenge for urban renewal is to reverse economic and social decay in poor districts and policy makers have to allow for interactions throughout the urban system.

[1] Rey and Montoury (1999), Le Gallo, Ertur, and Baumont (2003), and Le Gallo, Baumont, Dall'erba, and Ertur (2005) analyze such processes for regional economic growth.

Modeling spatial effects in hedonic housing price functions can provide new insights into at least three urban mechanisms which traditionally describe urban patterns: 1/ neighborhood effects and their impacts on location decisions, which mechanism refers to the assimilation of the quality of life, economic and social opportunity, and the type of neighborhood; 2/ spatial segmentation of urban space that can be associated with the occurrence of various housing sub-markets each with a specific housing value distribution and a local price formation mechanism; and 3/ spatial dependencies among sub-markets and the way they contribute to a global mechanism of housing price formation. These mechanisms are obviously interdependent and attention to spatial effects in terms of spatial autocorrelation, spatial heterogeneity, and spatial diffusion of random shocks improves urban planners' knowledge of these mechanisms. Our study may, however, be developed to better account for spatial heterogeneity since we have used an exogenous housing segmentation based on three types of area: deprived districts associated with social housing programs, the centrally located conservation area, and other districts. Such spatial segmentation fails to take account of the diffusion and concentration mechanisms emphasized in our studies. Spatial effects and neighborhood effects could be simultaneously defined by ESDA (Ertur et al., 2006) and yield, in a more endogenous way, the spatial heterogeneity to use in a hedonic housing approach. This will be investigated in a subsequent program.

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Notes

[1] Details are available upon request from the author.

[2] This matrix has been computed using GeoDa (095i).

[3] Computed with SpaceStat 1.90 (Anselin, 1999).

[4] Inference is based on the permutation approach with 9999 permutations.

[5] High (resp. low) means above (resp. below) the mean.

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

[7] The prefix L indicates the log transformation of the corresponding variable.

[8] According to the model, some slightly changes may be observed.

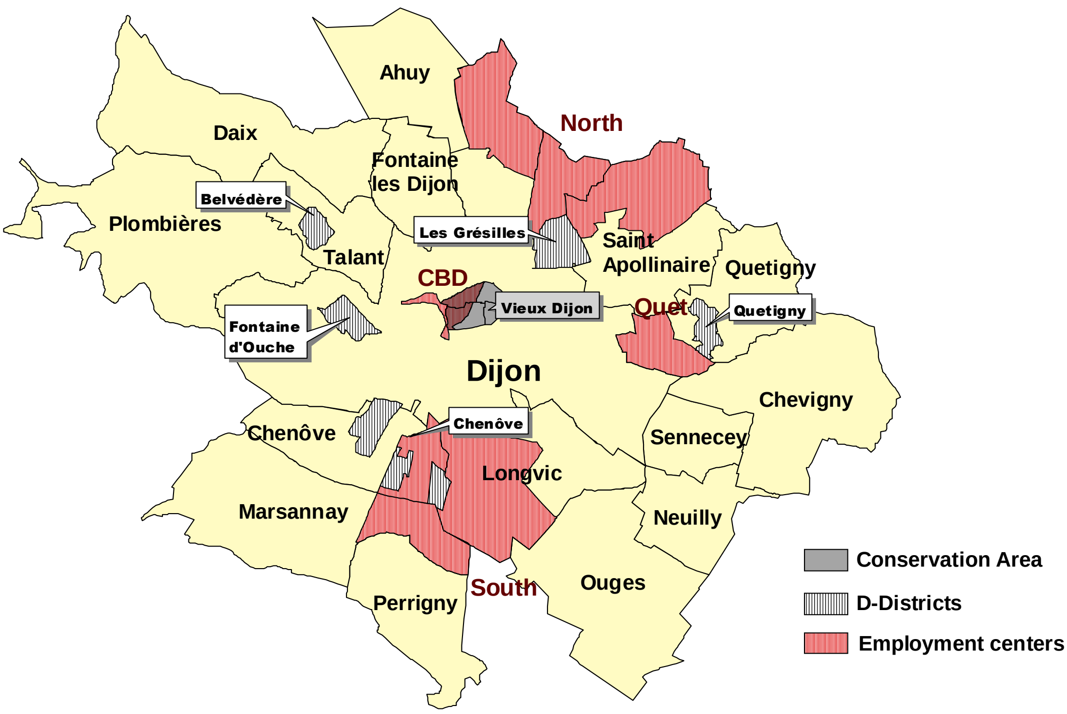
[9] The spatial diagnostics reported here are prepared with the weighted 7 nearest neighbors matrix $W_7(d_{ij})$. Complete results are available upon request.

[10] The decision rule advocates comparing the values of the LM tests and the associated p-values. Here, the values of the LMERR test and of its robust version R-LMERR are higher than the values of the LMLAG and R-LMLAG tests. The associated p-values are smaller for spatial error than for spatial lag.

[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 errors is assumed.

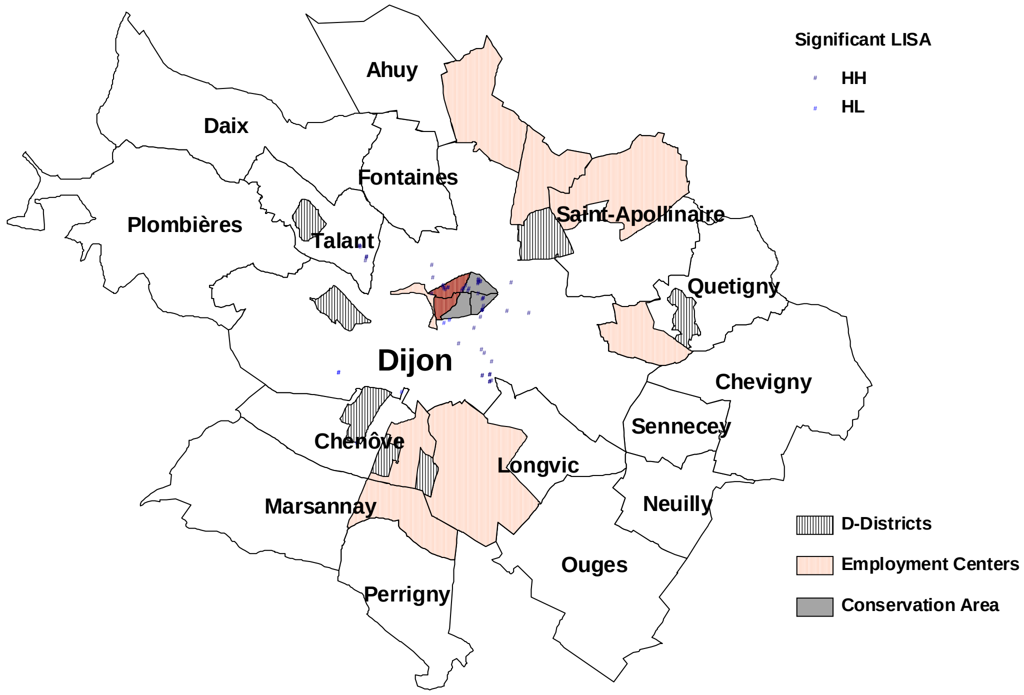
Map 1: The 114 IRIS of the COMADI

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



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*)

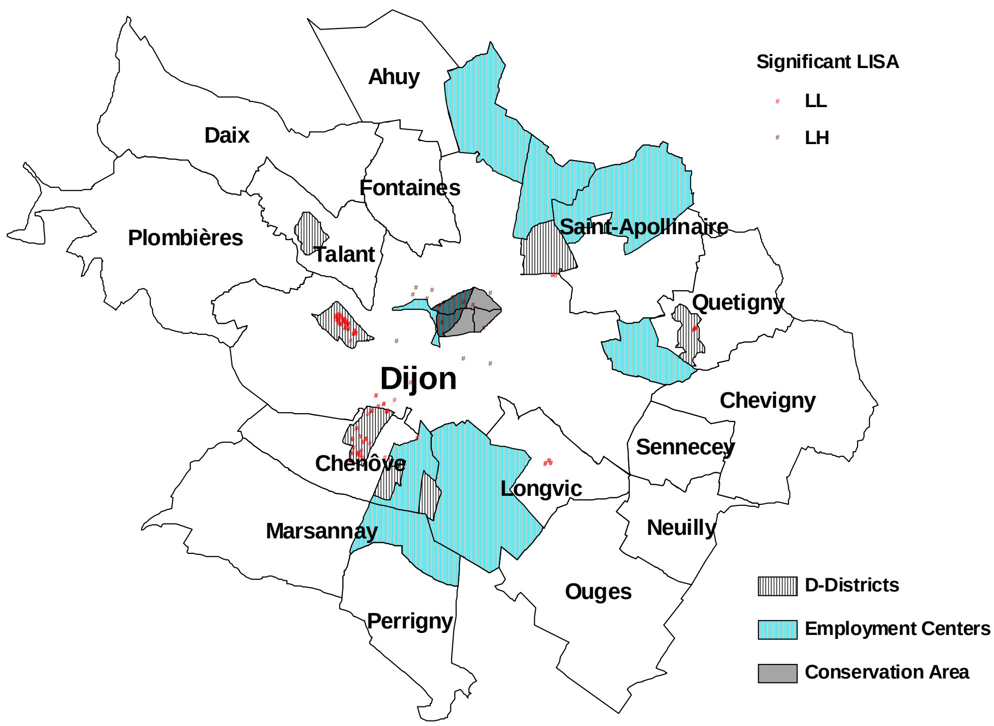


Table 1: Variables – Summary Statistics

Variable	Description and Unit	Mean (or nb*)	S.D. (or %*)
Structural attributes of apartments (measured on the sample of transactions)			
PRICE	Transaction price in € (before tax)	64 575	35 959
SURF	Floor space (m^2)	62	26
ROOM	Number of rooms	3	1.2
BATH	Number of bathrooms	1.3	0.2
TER-BAL	Dummy (=1 if the apartment has a terrace or a balcony and 0 otherwise)	*261	*17.2
CEL-LOFT	Dummy (=1 if the apartment has a cellar or a loft and 0 otherwise)	*1520	*100
BEF1850 (built before 1850)	Dummy (=1 if the apartment was built before 1850 and 0 otherwise)	*96	*6.3
YEARa_i-a_j (built between ai and aj)			
1850–1913	Dummy (=1 if the apartment was built between year a_i and year a_j and 0 otherwise).		
1914–1947		*126	*8.3
1948–1969		*118	*7.8
1970–1980		*479	*31.5
		*441	*29
AFT1980 (built after 1980)	Dummy (=1 if the apartment was built after 1980 and 0 otherwise).	*260	*17.1
Neighborhood Variables (status) *measured at the IRIS scale*			
UNEMP	Unemployment rate (%)	11.3	6.6
HIGHER-OCCUP.	% of higher management and professional occupations	15	10.7
INTERMEDIATE-OCCUP.	% of intermediate occupations	26.7	7.5
CLERICAL	% of clerical workers	31.3	9
MANUAL	% of manual workers	22.6	11.9
FOREIGN	% of non-French households	6.1	5.3
DENS-POP	Population density: Nb of inhabitants per acre	24.3	22.6
VACANT	% of vacant housing	6.9	4.9
HIGH-EDUC	Ratio: number of university graduates to number of people with no qualifications	1.27	1.64
Neighborhood Variables (urban development districts)			
D-District (Deprived District)	Dummy (=1 if the apartment is located in a D-District and 0 otherwise)	*178	*11.7
CONS-AREA (Conservation Area)	Dummy (=1 if the apartment is located in the Conservation Area and 0 otherwise)	*223	*14.7
Accessibility Variables			
DIST-CBD	Distance to the CBD (m)		
INV-MIN-SUBCENTER	Inverse distance to the nearest subcenter (m)		
MIN-DDistrict	Distance to the nearest D-District (m)		

Table 2. Summary statistics: Conservation Area and D-Districts

	Conservation Area	Chenôve	Fontaine d'Ouche	Grésilles	Quetigny	Belvédère	COMADI
Single-family House (%)	6.2	7.2	1.5	9	3	7	25
Apartment (%)	71.6	82.7	90.9	72.6	91.9	86.2	63.3
Major building period	Before 1948	1949 - 1974	1949 - 1974	1949 - 1974	1949 - 1981	1974 - 1981	
Vacancy rate (%)	13.4	7.1	5.1	16	3.7	2.5	6.9
Social housing (%)	5	67	51	78	63	65	22
Higher (%)	28.4	4.1	4.3	4.4	5.5	6.9	15
Intermediate (%)	27.7	14.3	17.4	16.2	20.2	21.2	26.7
Clerical (%)	22.1	35	39.5	32	36.6	41.9	31.3
Manual (%)	10.5	44.3	32.5	43.2	34.3	28.7	22.6
Unemployment rate (%)	9.9	18.8	11.4	11.8	7.5	11.1	11.3
Population density (per acre)	49.2	43.9	61.6	28.3	34.4	48.6	56
Ratio of immigrants	4.7	17.4	10.7	17.6	8.4	9.6	6.1
University graduate/no qualification	2.95	0.08	0.22	0.12	0.37	0.30	1.27
Distance to CBD (m)	0	3600	2700	2400	5000	3860	
Distance to the nearest subcenter (m)	4000	2000	4800	2700	500	5380	
Jobs (total %)	11.4	0.7	0.9	1.1	0.3	0.3	100

Table 3: Moran's *I* statistics for housing unit price distribution in 1999

W matrix	Moran's I	St. dev.	St. Value*	p value
$\bar{d}$ =250 m	0.3076	0.0113	27.7496	0.0001
k = 7 nearest neighbors	0.3687	0.0128	29.2316	0.0001
$W_7(d_{ij})$	0.4624	0.0228	20.5987	0.0001

** The expected value for Moran's I statistic is* $E(I) = -1/(n-1) = -6.6\times10^{-4}$ *(n = 1520)*

Table 4: Spatial association patterns (LISA) of housing prices

W matrix	none	HH	LL	HL	LH
$W_7(d_{ij})$	-	504	570	206	240
$\bar{d}$ =250 m	33	518	487	172	310
k = 7 nearest neighbors	-	519	543	191	267

Table 5: Significant spatial association patterns (LISA) in urban development areas
(*Bonferroni's level of significance*)

	HH			LL			HL			LH			Total			nb
	Wnn	$\bar{d}$	*nn*	*Wnn*	$\bar{d}$	*nn*	*Wnn*	$\bar{d}$	*nn*	*Wnn*	$\bar{d}$	*nn*	*Wnn*	$\bar{d}$	*nn*	
CVA	28	34	41				4			5	24	5	37	58	46	223
D-Districts				59	86	96		2	2				59	88	98	178
Other Areas	26	37	28	7	11	17	4	1	5	7	15	8	44	64	58	1119
Total	54	71	69	66	97	113	8	3	7	12	39	13	140	210	202	1520

Wnn is for the weighted 7 nearest neighbors matrix $W_7(d_{ij})$ *,* $\bar{d}$ *is for the threshold* $\bar{d}$ *=250 m binary matrix and nn is for the 7 nearest neighbors binary matrix.*

Table 6: OLS estimates for the hedonic housing price function

Dependent Variable: L-PRICE

	Model 1		Model 2		Model 3		Model 4	
VARIABLE	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value
CONSTANT	9.1453	0.0000	9.1963	0.0000	9.1758	0.0000	8.8212	0.0000
L-SURF	0.9333	0.0000	0.9364	0.0000	0.9225	0.0000	0.9371	0.0000
BATH	0.1199	0.0000	0.1228	0.0000	0.1152	0.0000	0.1185	0.0000
AN5013	-0.0808	0.0006	-0.0705	0.0022	-0.0836	0.0002	-0.0705	0.0021
AN1447	-0.0390	0.0998	-0.0330	0.1576	-0.0526	0.0223	-0.0404	0.0811
AN7080	0.0743	0.0000	0.0901	0.0000	0.0644	0.0000	0.0845	0.0000
AFT1980	0.2691	0.0000	0.2588	0.0000	0.2389	0.0000	0.2556	0.0000
CELLOFT	0.0309	0.0041	0.0237	0.0269	0.0282	0.0074	0.0228	0.0319
TERBAL	0.0573	0.0003	0.0628	0.0001	0.0536	0.0005	0.0544	0.0005
L-DCENT	-0.0653	0.0000	-0.0553	0.0001	-0.0308	0.0246	-0.0462	0.0016
MIN-DD	0.0095	0.0000	0.0043	0.0001	0.0051	0.0000	0.0033	0.0026
C-AREA			0.0017	0.9377			-0.0094	0.6909
D-District			-0.2064	0.0000			-0.1639	0.0000
Inv-MinSub			-64.7799	0.1708				
L-Highschool					0.0807	0.0000		
L-Foreign					-0.0187	0.2856		
L-DensPop					-0.0117	0.1966	0.0227	0.0265
L-Vacant					-0.0084	0.6132	-0.0095	0.5645
L-Intermediate-Occup.							0.1439	0.0001
L-Clerical							-0.1047	0.0016
R^2	0.791		0.799		0.805		0.803	
R^2-adj	0.790		0.797		0.803		0.801	
LIK	67.996		95.941		120.300		113.797	
BIC	-55.400		-89.311		-130.704		-103.043	
AIC	-113.991		-163.882		-210.601		-193.593	
σ^2	0.054		0.052		0.050		0.051	
Diagnostic for spatial dependence								
MORAN	10.933	0.0000	9.549	0.0000	8.218	0.0000	8.896	0.0000
LMERR	115.771	0.0000	86.278	0.0000	63.100	0.0000	73.300	0.0000
R-LMERR	63.012	0.0000	44.847	0.0000	35.831	0.0000	38.988	0.0000
LMLAG	54.546	0.0000	43.633	0.0000	27.974	0.0000	35.932	0.0000
R-LMLAG	1.787	0.1813	2.202	0.1379	0.705	0.4010	1.621	0.2030

Notes: LIK is the value of the maximum likelihood function. AIC is the Akaike (1974) information criterion. BIC is the Schwarz (1978) information criterion. 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 variables and R-LMLAG is its robust version (Anselin and Florax, 1995; Anselin *et al.*, 1996).

Table 7: Spatial Error Model estimates for the hedonic housing price function

Dependent Variable: L-PRICE

	Model 5				Model 6			
	SEM-ML		SEM-GMM		SEM-ML		SEM-GMM	
VARIABLE	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value
CONSTANT	9.1053	0.0000	9.1044	0.0000	8.6420	0.0000	8.6405	0.0000
L-SURF	0.9293	0.0000	0.9293	0.0000	0.9406	0.0000	0.9406	0.0000
NBSDB	0.0999	0.0000	0.0998	0.0000	0.1039	0.0000	0.1038	0.0000
AN5013	-0.0669	0.0029	-0.0667	0.0030	-0.0583	0.0097	-0.0582	0.0098
AN1447	-0.0494	0.0319	-0.0493	0.0321	-0.0411	0.0743	-0.0411	0.0742
AN7080	0.0617	0.0002	0.0617	0.0002	0.0750	0.0000	0.0750	0.0000
AFT1981	0.2252	0.0000	0.2251	0.0000	0.2353	0.0000	0.2351	0.0000
CELLOFT	0.0292	0.0053	0.0292	0.0052	0.0248	0.0180	0.0249	0.0179
TERBAL	0.0549	0.0005	0.0549	0.0005	0.0568	0.0003	0.0568	0.0003
L-DCENT	-0.0301	0.0652	-0.0301	0.0658	-0.0433	0.0065	-0.0433	0.0066
MIN-DD	0.0001	0.0000	0.0001	0.0000	0.00003	0.0119	0.0000	0.0120
D-District					-0.1530	0.0002	-0.1529	0.0002
L-Highschool	0.0757	0.0000	0.0757	0.0000				
L-Foreign	-0.0161	0.4364	-0.0161	0.4382				
L-DensPop	-0.0067	0.5238	-0.0067	0.5286	0.0213	0.0747	0.0213	0.0754
L-Vacant	-0.0072	0.7106	-0.0072	0.7118	-0.0047	0.8095	-0.0046	0.8120
L-Intermediate					0.1616	0.0001	0.1618	0.0001
L-Clerical					-0.0741	0.0426	-0.0738	0.0439
λ	0.2186	0.0000	0.2208	0.0000	0.2332	0.0000	0.2352	0.0000
R^2	0.7996		0.7995		0.7937		0.7936	
Sq.corr	0.805		0.8045		0.803		0.8027	
LIK	165.472				165.613			
BIC	-221.048				-214.003			
AIC	-300.945				-299.226			
σ^2	0.047		0.0471		0.047		0.0471	
LMLAG*	3.275	0.0704			2.923	0.0873		

Notes: SEM-ML is the 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 (1978) information criterion. LMLAG* is the Lagrange multiplier test for an additional spatially lagged endogenous variable in the spatial error model (Anselin, 1988)