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Hedonic estimation of the green value of residential housing.

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Abstract

Managing the energy demand in the residential sector could be achieved by the promotion of energy efficiency buildings. We assume that households adopting a green behavior are willing to pay a greater price to access "green" housing. This added value is called the "green value". This paper studies the impact of the energy efficiency rating of a house, as certified by the *Diagnostic de Performance Energetique (DPE)*, on housing prices. In order to do this, the hedonic price method has been applied to the real estate market - apartments and houses - in the urban area of Dijon from January 2013 to December 2014. To control for spatial effects we estimate a Spatial Durbin Model. The results indicate that the impact of DPE is mostly observed for the least performing classes. This negative impact is smaller for the apartment market. We also show that proximity to green amenities - outside the cities - has a positive effect only for house market.

JEL classification : Q48, Q51, C21, R21

Keywords : Housing Green Value, Energy Performance Certificate, Residential Housing, Spatial Hedonic Models, Spatial analysis.

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1 Introduction

The energy transition and environmental concerns strengthen the objective of strong reductions of carbon dioxide emissions and require significant changes in consumption in the energetically dependent sectors. Since the residential sector accounts for more than 25% of final energy consumption in 2016 in the European Union, one way for public policies is to promote energy efficient buildings on real estate markets. Energy labels or green certificates introduced on the real estate markets at the beginning of the 2010's help to overcome the problem of information asymmetry in energy efficiency and in related green attributes of dwellings. As households adopt green behaviors, the demand for energy efficient housing, would increase and an additional value for environmental efficient dwellings, called "*green value*" would be observed. The empirical literature has demonstrated that such a premium does exist for green housing (see for example Kok and Kahn, 2012; Fuerst et al., 2014).

A recent meta-analysis of 79 estimations of commercial and residential real estate green-value (Fizaine et al., 2017) confirms the impact of energy labels and green certificates on the price of the dwellings. However, this meta-analysis highlights the lack of empirical studies taking care of spatial dependencies in the estimation of the hedonic housing green value even though spatial attributes and spatial interactions are major characteristics of reale state markets facing environmental (Maslianskaïa-Pautrel and Baumont, 2016). A lack of french real estate market studies has been pointed too.

Our paper aims to overcome these limits. From a set of georeferenced data on the urban area of Dijon (France), we produce three types of spatial attributes to control for spatial effects impacting the real estate prices: (*i*) local amenities i.e. environmental attributes present in the surroundings of the dwelling, (*ii*) the distance to labour markets in order to measure the accessibility to jobs and (*iii*) the distance between each pair of housing to capture the spatial diffusion process of real estate transactions in our sample. We estimate a spatial hedonic model to explicitly take into account spatial dependencies between dwellings.Ignoring spatial dependencies could lead to biased results overestimating or underestimating the green value because it ignores a spatial multiplier effect, encompassing the impact of the characteristics of the other dwellings and of their location on the market. The best spatial specification to estimate in our case is a Spatial Durbin Model which gives the household's marginal willingness to pay for the housing attributes.The green value of the dwelling is proxied by the French label DPE (*Diagnostic de Performance Energétique*). Our results show a significant implicit prices for housing according to its level of energy performance. We find three types of impacts. First,the implicit prices are negative for housing with low energy performance certificates. Second,the impacts differ according to the type of housing market. For the apartments, this depreciation goes from 6.8 to 11.5% for the lowest level of energy performance. For houses, this loss is much more important and goes from 16.5 to 30% for the lowest level of the DPE. Finally, we also find a positive premium of around 9.75% in the medium energy performance distribution compared to lower level.

The remainder of the paper is organized as follows. Section 2 presents the twofold research positioning of the green value estimation through an empirical literature survey and the spatial hedonic evaluation methodology. Section 3 presents our study area, data, and variables. Our empirical strategy is developed in Section 4. Results are discussed in Section 5 which gives the impacts of the DPE label on dwelling prices. The last section gives some concluding remarks and implications for future research.

The remainder of the paper is organized as follows. Section 2 presents the literature estimating the green value. Section 3 presents our study area, data, and variables. Our empirical strategy is developed in Section 4. Results are discussed in Section 5 which gives the impacts of the DPE label on dwelling prices. The last section gives some concluding remarks and implications for future research.

2 Green value estimation

2.1 Existing literature and motivations

Following the energy crisis in the 1970s, there was a rapid development of a broad literature trying to evaluate the effect of energy efficiency on building value (Dinan and Miranowski, 1989; Johnson and Kaserman, 1983; Laquatra, 1986; Quigley and Rubinfeld, 1989). As pointed out by Fuerst et al. (2015), many of these studies lack of consistent data (small sample size, lack of representativeness), but showed significant and positive results. In the 2000s the concept of green value was established by scientists, while policymakers were developing energy labels. In the European Union, the directive on the energy performance of buildings[1] sets the importance of energy label in the achievement of the energy transition. Meanwhile, a second wave of empirical papers estimated the value of energy efficiency or the green value using the energy labels as proxies. For instance, Pfleger et al. (2011) compare a random sample of new houses labeled Energy Star®[2] with a sample of houses as similar as possible without this label. They show that labeled houses are selling faster and for higher prices than unlabeled houses. However, they do not quantify this market advantage of the Energy Star label.

Two methods are generally used in the literature to estimate the green value: discrete choice experiment (DCE) and hedonic evaluation (HE) ones. DCE allows taking into account multiple factors influencing the decision to invest in energy-efficiency. Therefore, it also enables to estimate the willingness to pay for each energy-savings measure. For example, Banfi et al. (2008) run a choice experiment to estimate the willingness to pay (WTP) for three types of energy-saving measures using both for retrofit building or new ones: window insulation, facade insulation, and ventilation system. The WTP is estimated both for renovation and new buildings, and concerns the housing owners as well as tenants. The results show that "*house buyers and apartment tenants have a similar WTP for the case*

[1]See Directive 2010/31/EU of the European Parliament and of the Council of 19 May 2010 on the energy performance of buildings - EPBD.

[2]Energy Star is an American certification for energy-efficient buildings. For more information,: https://www.energystar.gov/

of new buildings". It is about 3% for enhanced facade insulation and varies from 4 to 12% for the ventilation system. While the window insulation is not valued for new buildings, in existing ones, "*the willingness to pay is particularly high for window improvements.*" It is about 13% for both homeowners and tenants.

Using DCE methods to reveal household preference is also recommended when the share of energy-performant building is low. However, the DCE method, as any stated preference methods, is expensive to set up and the results are subject to bias in the declaration of preferences and in the limited numbers of alternative choices proposed by the survey.

On the contrary, hedonic evaluation requires larger datasets. It can be easily implemented in both the residential and tertiary sectors and allows controlling for a large set of variables such as neighborhood, location, accessibility, and others. If energy-savings buildings are spread in the housing markets, the hedonic price method offers the opportunity to work on a large dataset of dwelling transactions.

Most of the hedonic studies estimate the green value by taking green labels as a proxy variable. This literature used to be mainly focused on the office buildings as there is an abundant source of data especially the US ones (for exemple, Eichholtz et al., 2010; Dermisi, 2009; Fuerst and McAllister, 2011; Deng et al., 2012; Eichholtz et al., 2013; Miller et al., 2008). All those studies estimate the impact of green labels on prices or rents. The results suggest that being a certified building increases the rent and has a positive impact on the selling price. Estimated values are highly heterogeneous according to the type of green label (for example, LEED [3] or Energy Star for the USA) or to the estimation method used. The results also show that the positive impact of green label significantly varies across different levels of certification: *ceteris paribus* the highest levels are valuated more then lower ones (see for exemple, Deng et al., 2012). Eichholtz et al. (2010) also show that "*The premium is negatively related to the location premium for a building, within and between cities: a label appears to add more value in smaller markets and regions and in the more peripheral parts of larger metropolitan areas, where location rents are lower.*"(page 33).

For the residential market, most of the studies were realized in the last decade and use the hedonic method as well. It appears that the green values are lower for the housing market than for the office one. For instance, Brounen and Kok (2011) estimate a green premium of 3.7% for dwellings using a dataset of 177 000 transactions in the Netherlands. Overall, there is not an agreement about the green value. In the literature, estimates range from non-significant results (for instance Davis et al., 2015) to 20% (Yoshida and Sugiura, 2011).

Due to the early emergence of energy labels in North America (LEED in 1998 and Energy star in 1999), the first studies have mainly concerned the USA. Recently, there was a growing number of studies for European countries (for instance Davis et al., 2015; Chegut et al., 2016): European certificates known as Energy Performance Certificate were

[3] LEED stands for Leadership in Energy and Environmental Design. LEED was created in 2000 and is a worldwide energy-efficiency rating system for buildings. For more information: https://new.usgbc.org/leed

standardized and became mandatory. In France it is the label known as *DPE (Diagnostic de Performance Energètique).* Few papers concern Asian countries: papers finding a green value though energy labels are still nascent or absent (Addae-Dapaah and Chieh, 2011; Deng and Wu, 2014). Although energy management is an important matter for this continent, we haven't found any papers for Africa.

As far as we know, only one academic study estimates the green-value for French housing data (Mudgal et al., 2013)[4]. This report, made by the European commission, compiles the results found for 7 countries. For the French case, the study concerns a sample of 3 400 housing transactions collected in Marseille and Lille. For Marseille, the authors found an increase of 4.3% of the value for "*each one-letter improvement in a property's energy label*", and 3.2% for dwellings in Lille.

Since these papers are using labels as a proxy for energy efficiency variable, they are in fact measuring a green value integrating multiple aspects of environmental housing: energy efficiency, comfort, image, reduction of vacancy... Even if green valuation aims at measuring all the environmental services brought by a dwelling, the energy certificate is a good proxy as it synthesizes the available information on the energy-efficiency characteristics of the dwellings. This label provides clear and direct information about the energy-efficiency of the dwelling, which will be in return found in the price.

However, energy labels have two drawbacks. First of all, there are various labels throughout the world and even within each country. The methods employed to calculate energy-efficiency diverge between the labels and results can be presented in different ways: for example, A to G for the EPC, Platinum/Gold/Silver/Certified for LEED. Some certificates are mandatory, like the EPC, while others are not (for instance LEED). These differences affect the comparability of green values and reduce the readability of the energy performance of housing. The second drawback is that the energy cost of living in a given dwelling is not provided by an, so it's difficult to know whether consumers correctly consider the energy costs when they buy a dwelling.

Finally, Dermisi (2009) and Jaffe et al. (2012) empirically show the importance of taking into account geographic assets as energy prices and weather affect the green value.Jaffe et al. (2012) matched data on the local weather to the characteristics of the building. Indeed the heterogeneity of the local real estate markets should be taken into account. Going further, Dermisi (2009) uses a spatial error model to take into account spatial autocorrelation of the residuals. The use of a spatial model is important as spatial autocorrelation and spatial heterogeneity can lead to inefficient estimator or to biased estimates. Overall, the green value literature lacks of spatial analysis. This subject will be deeply discussed in the next section.

[4]Note that a non-academic report has estimated the green value for France: *Etude économique sur la valeur verte de l'immobilier de logements*, Décember 2011, 83 pages

2.2 *Spatial hedonic evaluation*

The hedonic property value model is based on the seminal work of Rosen (1974). As stated by this model, one can estimate the price of non-market goods by observing the equilibrium in the housing market. A dwelling is a differentiated good which can be considered as a set of its attributes. The optimal choice is therefore determined by the choice of dwelling's attributes which maximize the household's utility. The regression of housing prices on their attributes can reveal consumers' marginal willingness-to-pay (MWTP) for particular dwelling characteristic and can be thought as its implicit price.[5]

Considering the following hedonic equation :

$$\mathrm{P} = \alpha i_n + X\beta + \epsilon, \tag{1}$$

where P is a price of a dwelling, X is a matrix of explanatory variables, β is a vector of associated coefficients, i_N is an $N \times 1$ vector of ones associated with the constant term parameter α, ϵ vector of error terms.[6]

According to Baumont (2009), the matrix X is composed of three bundles of characteristics, $X = (H; N; A)$, corresponding respectively to structural attributes, neighborhood variables and accessibility variables. Structural or intrinsic attributes, H, describe the physical characteristics of the housing and satisfy household preferences for residential services (Muth, 1969). The Energy Performance label is precisely part of these characteristics. The second set of attributes, N, includes neighborhood variables depicting the quality of amenities and the economic and social characteristics in the neighborhood of the dwelling. We can talk about local extrinsic attributes revealing the household's "social" preferences (i.e. the type of society and the place where they want to live). The third bundle, A, is composed of accessibility variables to major markets. We speak of global extrinsic attributes - i.e. across the entire location area - satisfying household preferences for markets integration (Bajari and Kahn, 2005).

The second and third bundles, neighborhood variables and accessibility variables, are outcomes of the household's choice of location. This choice of location allows for the household to enjoy surrounding amenities and the proximity to services and to working locations. These choices shape the housing market which in return leads to spatial dependencies.

Spatial dependencies refer to spatial autocorrelation and spatial heterogeneity. It means that the housing prices observed in one place may not be independent of the housing prices observed in neighboring areas. The study of spatial dependencies in the real estate markets is well documented and, in some way, has accompanied the emergence of spatial econometrics in the 1990s (Dubin et al., 1999; Dubin, 1992) and its developments still now (Baumont, 2009; Thanos et al., 2016). Among the main sources of spatial dependence in the housing price distribution we give the following ones. Housing located in the same

[5]Let us note that the obtained MWTP can then be used in a second step of the hedonic evaluation, to calculate the demand for this characteristic. In our paper we only focus on the first stage of the procedure.

[6]In our estimates, we use a log-log specification of the hedonic equation (1), which is very often used specification in hedonic studies. The OLS estimated coefficient can be interpreted as elasticity of the corresponding characteristic.

district share the same amenities and then could have the same implicit prices. Housing built at the same period have the same characteristics (the size of the rooms, the level of energy performance ...) that implies similar implicit prices and their locations generally follow the spatial extension of the city : they are located in the same available places. Finally, as stated by urban models, housing located at the same distance of the job district could have the same unit prices.

Technically, to deal with the spatial dimension requires the description of a spatial interaction pattern, defined by the spatial weight matrix W, which indicates the way each observation is connected to each other and gives the value of the intensity of the connections.

Formally, for N observations (dwellings), the spatial weights matrix,W, is a squared $N \times N$ matrix, the generic term is noted w_{ij}, where i and j denote observations. $w_{ij} \neq 0$ if and only if the observations i and j are considered as neighbors, and zero otherwise. By convention, $w_{ii} = 0$ (Anselin, 1992).

For a variable z, Wz is its spatial lagged variable. Wz is a weighted linear combination of the values of the variable x observed for a set of neighboring dwellings. Three types of spatial lagged variables can be introduce to model spatial interactions between dwellings into the hedonic regression (1).

Endogenous spatial lag variable, WP, allows to estimate a spatial autoregressive coefficient ρ indicating the intensity of the impact of neighboring house prices on the price of the observation itself. The effects of such endogenous interactions are modeled by a SAR Spatial Autoregressive Model :

$$\text{SAR Model: } P = \rho WP + \alpha i_n + X\beta + \epsilon. \tag{2}$$

Exogenous spatial lag variables WX, allow the modeling of exogenous interaction effects and to estimate θ, a $K \times 1$ vector of parameters corresponding to the exogenous variables. The values of θ can be viewed as the intensity of the impact of neighboring dwelling attributes on the price of the observation itself. Spatial lag of exogenous variables are usually modeled in the SLX Spatial explanatory lagged model :

$$\text{SLX Model: } P = \alpha i_n + X\beta + WX\theta + \epsilon. \tag{3}$$

The error lag, noted $W\epsilon$, allows the modeling of the spatial dependence of nuisance in a SEM - Spatial Error Model - specification (equation (4)). The estimated value of the spatial parameter λ indicates the intensity of the dependence between the residuals of the regression.

$$\text{SEM: } P = \alpha i_n + X\beta + \epsilon, \quad \epsilon = \lambda W\epsilon + u. \tag{4}$$

The SEM specification is useful to control for the omission of spatial autocorrelated variables (Anselin and Le Gallo, 2006). Estimated values are then based on the good statistical inference.

In the Spatial autoregressive model (SAR), Spatial explanatory lagged model (SLX) and Spatial error model (SEM), only one type of spatial interaction is introduced: endogenous interaction, exogenous one or of nuisances respectively. It is possible to combine several types of interactions. The Spatial Durbin Model (SDM) combines exogenous interactions and endogenous ones (equation (5)) and the Spatial Durbin Error Model (SDEM) combines exogenous interactions and nuisance interactions (equation (6)).

$$\text{SDM: } P = \rho W P + \alpha i_n + X\beta + WX\theta + u, \tag{5}$$

$$\text{SDEM: } P = \alpha i_n + X\beta + WX\theta + \epsilon, \quad \epsilon = \lambda W \epsilon + u \tag{6}$$

Those spatial specifications are widely used in hedonic valuation of environmental amenities (Votsis, 2017; Maslianskaïa-Pautrel and Baumont, 2016; Mihaescu and vom Hofe, 2013; Fernandez-Aviles et al., 2012; Bin et al., 2011; Anselin and Lozano-Gracia, 2008), and of social effects of neighborhoods (Baumont and Legros, 2013; Baumont, 2009). One study estimates the impact of an energy label using a spatial hedonic model (Dermisi, 2009). He estimates a Spatial Error Model to study the impact of the LEED certificate on commercial buildings in the USA.

Spatial hedonic models may provide information about spatial interactions, that is the way spatial lagged prices and/or spatial lagged attributes design the market. However, the introduction of these lagged variables in the regression (1) modifies the estimators and requires rigor in the interpretation of the estimated coefficients in order to evaluate the implicit prices of housing attributes (Halleck Vega and Elhorst, 2015). Only the most recent literature deals with these problems. A synthesis proposed by Maslianskaïa-Pautrel and Baumont (2016) shows how the different types of spatial interaction patterns impact the estimation of the implicit prices (cf Table 1). The choice of spatial specification is not neutral and questions the robustness of the estimated results and the selection of the spatial model.

Following the methodology developed by Maslianskaïa-Pautrel and Baumont (2016), we are using two approaches for selecting the appropriate spatial model. The first one, *Specific-to-General* approach, consists in testing for spatial dependence in a non-spatial equation, and to perform a series of tests for the presence of a spatial dependence. If spatial autocorrelation is confirmed (Moran'I test), we can discriminate between two forms of spatial dependencies - spatial autocorrelation of errors - SEM - or endogenous spatial lag - SAR (Lagrange Multiplier tests: LMERR and LMLAG, and their robust versions, R-LMERR and R-LMLAG). When the choice of the SEM model is suggested, the Common Factor test should be used to choose between the SEM specification and its extensive form as a SDM specification.[7] The same approach can be used by starting with a SLX specification. Figures 1(a) and 1(b) display a step by step process.

A *General-to-Specific* approach, discussed for example by Halleck Vega and Elhorst (2015), involves to start with the most general model and to test if these models are more

[7] See Anselin and Florax (1995); Anselin et al. (1996) for more detail about rule decision based on Lagrange Multiplier Tests, and Mur and Angulo (2006) about the Common Factor test.

appropriated than different constrained specifications, by using Likelihood Ratio tests (LR test) on spatial parameters ρ, λ, θ. Figure 1(c) shows this approach.

Once the appropriate specification is chosen, the estimation of implicit prices of housing attributes is obtained using the estimated values of the parameters as detailed in Table 1. Since our goal is to develop a robust evaluation of the implicit price associated with the energy label, we apply this methodological framework to our case study.

3 Study area and data

3.1 Urban area of Dijon (France)

Our empirical model is developed for the urban area of Dijon (see Figure 2), located in the east of France in the Region Bourgogne Franche-Comté. The urban area spreads over 3 339 km^2 and encompasses 295 cities.[8] With 380 236 inhabitants and 167 730 jobs[9], the urban area of Dijon is the largest urban areas of the Bourgogne-Franche-Comté. During the last decade, its population increased due to a surplus of births over deaths, and employment is expanding, especially in the tertiary sector and in the metropolitan functions. The city of Dijon is the core of the *Urban Center* where 153 000 people live. The *Grand Dijon* is a cluster of municipalities and is the administrative level at which main public facilities like public urban transportation and metropolitan public services such as State institutions of higher education or main cultural services are offered. The *Grand Dijon* includes 24 municipalities and 248 028 inhabitants. Outside the *Grand Dijon*, the urban area is composed of rural districts excepted for a bundle of small cities. The population density strongly decreases from the core to the urban area fringe: from 3 786 inhabitants per km^2 in Dijon, to 476 inhabitant per km^2 for the first ring and only 36 inhabitants per km^2 in the periphery.

According to the 2013 census data, 71 000 of houses in the study area are occupied by their owners, which corresponds to 88% of the stock of the houses used as main homes. For apartments, the owner-occupied percentage is lower than for houses: about 33% of 31 000 apartments are used as the main home. It is not surprising to observe that the *Grand Dijon* attracts mainly young people, students or workers. Dijon attracts students from the surrounding areas. Many small-sized apartments have been developed to welcome them creating at the same time a higher number of rented apartments. Families prefer living in single houses and often choose to live in the cities surrounding Dijon or in more distant towns where they can find private and public facilities while remaining close to Dijon by the road or by the train. The eastern and the northeastern sectors of the urban area are the main beneficiaries of these residential choices.

Eventually, the Dijon urban area is a territory with various natural amenities. A large

[8]INSEE defines an urban area as a group of contiguous municipalities encompassing an Urban Center (*Pôle Urbain*) providing at least 10 000 jobs surrounded by a ring of suburban municipalities (named *Couronne Périurbaine*) for which at least 40% of employed resident population works in the Urban Center or in the suburban municipalities.

[9]Source : population census of 2013, INSEE RP-2013

part of the territory is occupied by agricultural land and forests. There are many rivers and lakes across the territory with the biggest being the Saône crossing the area from the south, and the Ouche river going through Dijon. In the urban and peri-urban areas, there are many parks and other open spaces offering various leisure and recreative activities. Nevertheless, there is no exceptional natural amenity in the study area such as mountains or a seashore. We could qualified the study area as quite homogeneous regarding to natural amenities.

One of the economic conditions necessary to obtain a green value using the hedonic evaluation is a stressless real estate market. Indeed, when supply is higher than demand on the real estate market, the cheapest dwellings are sold and the others remain vacant. The prices of the more efficient dwellings, here the green ones, must come down in order to be sold. If there is a lack of supply, all dwellings are sold or rented at high prices, whatever their characteristics. As a consequence, green characteristics can be a discriminating factor for buyers only for a stressless real estate market. For our case study, the housing market was stable in the urban area over the past five years, with a good dynamic and with out too much tension as the supply satisfies the demand.

3.2 Data

The data on real estate transactions come from the base PERVAL established by the Marché Immobilier des Notaires MINOT.[10] The sample includes single-family houses and apartments, sold from January 2013 to December 2014. The choice of this period is motivated by the French legislation about *DPE* label (*Diagnostic de Performance Energétique)*. The energy performance certificate *DPE* has been established in 2006 with the obligation to analyze the energy efficiency of a building before the property purchase. The publication of this label on the real estate ad is mandatory since 2010. We assume that in 2013 and 2014 households became accustomed to the publication of the *DPE* label and began to consider it as a signal of the housing's energy quality. In the PERVAL database, such information is available for 1 467 apartments and 1 082 houses which were purchased in 2013 and 2014. For each transaction, we extracted data on the price, the intrinsic characteristics and the precise location at the land parcel of the dwelling.

A first evidence concerns the spatial distribution of observations which is very different between houses and apartments. Houses are distributed throughout the urban area (Figure 3). There is a greater density of transactions in the central districts of the urban area (Grand Dijon) and a more homogeneous distribution of transactions over the rest of the urban area. In contrast, the apartments (Figure 4) are mainly concentrated in the urban center and virtually absent in the rest of the urban area. Therefore, these elements lead to consider a different spatial modeling for each type of housing in particular to define the spatial interactions between observations (see Section 4).

Among the intrinsic characteristics, the variable of interest is the energy performance

[10] Source : "*Notaires de France - base de données PERVAL" 2013 and 2014. Data integrated into the base on the 18/06/2015. Geographic area: 295 cities of Dijon urban area.*

label (*DPE*) which has 7 levels from A for the best energy performance to G for the worst one. The DPE labeling depends heavily on the successive French Thermal Regulations which have followed one another from 1974 to 2012. Thermal regulations draw their name from their year of implementation: the first one RT1974 applied in 1975 after the first oil shock and the last one RT2012 applied in 2013. Each new Thermal Regulation RT1974, RT1988, RT2000, RT2005 and RT2012 applied to all the new constructions respectively built after 1975, 1988, 2000, 2005 and 2012. If housing was not renovated nor transacted, its corresponding levels of DPE are the followings: levels G and F for RT1974, level E for RT1988 and RT2000, levels D, C or B for RT2005 and finally level A for RT2012. In the PERVAL database, 1980 is the first construction period after the first French Thermal Regulations RT 1974. A dummy variable $Post1980$ indicating whether the housing was built after 1980, was then added to intrinsic characteristics for both houses and apartments.

Estimating an average one-letter improvement implies that the premium is linear for each energy class. Yet, we can think that the effect of one-letter improvement may differ according to multiple factors: the scarcity of the letter, each class hasn't the same energy range (for instance 40 kW/m2/year for the class B vs 60 kW/m2/year for the class C), and we can think that consumers are less sensitive to the differences between letters on the middle of the ladder than on the top or on bottom. This is why in our empirical study we prefer to give a result for each letter.

The distributions of the energy performance certificate, rating from A to G, for each type of dwelling are presented in Table 2 and Figure 5. We observe that the distributions of the *DPE* are similar for houses and apartments. Unsurprisingly, there are more observations corresponding to high energy consuming categories (from D to G) than to the energy performing categories A,B or C. This reflects a relatively old housing stock both in terms of construction and in terms of thermal regulation. However the categories with the highest frequencies are the "middle ones", D and E like in most of the countries (Brounen and Kok, 2011; Mudgal et al., 2013).

In our sample, 70% of the houses and 77% of the apartments have a middle DPE, like in Fuerst et al. (2015) where C D and E represents more than 90% of their sample. Since only the housing transactions are recorded in the Perval Database, newly constructed dwellings are less likely to be sold and there are few dwellings withe DPE A and B in our sample. In that case, the literature suggests to group them into a single category Fizaine et al. (2017). Finally, the variable DPE is a qualitative variable with six modalities, and for the estimates, we use the modality D as reference.

Other intrinsic characteristics obtained from the PERVAL database are: living space (*LivSp*), number of rooms (*NbRoom*), number of parking lots (*NbPark*).[11] These variables are common to the samples of houses and apartments. For the house sample we also get the land area (*LandAr*), the number of floors (*NbFloor*) and the number of bathrooms (*NbBath*). For the apartment sample the variable *Floor* indicates the floor of the building

[11] In fact, living space and the number of rooms are correlated (correlation = 0.86), and then we follow the recommandations of many hedonic evaluation and we do not consider any more the variable *NbRoom* in the hedonic equation.

where the apartment is located.[12]

Concerning the neighborhood variables, data are extracted from the land use base *CORINE Land Cover 2012*[13] and of *Permanent Base of Equipment* (BPE, Insee[14]). We build the environmental variables and the accessibility variables using data obtained with GIS technics. More precisely, we assign to each dwelling a variable of proximity to green amenities ($DistGreenAm$) and a variable of proximity to blue amenities ($DistBlueAm$). Green amenities include forests and parks, with "$DistGreenAm$" being the Euclidean distance to the closest of these amenities. We considered as blue amenities rivers, lakes and ponds, with "$DistBlueAm$" being the Euclidean distance to the closest of these amenities. In addition, we assign to each dwelling the equipment rate *EqRate* of the district where the dwelling is located. We extract from The *Permanent Base of Equipment* database the following equipments: schools, cultural and sport infrastructures, and health facilities.

A district corresponds to the *IRIS*, a statistical unit defined by INSEE, which groups together 2000 inhabitants. Finally, we compute for each dwelling the distance to the closest disadvantaged district ($DistDD$). The population living in a French disadvantaged district, known as *Zone Urbaine Sensible*, is characterized by a high level of unemployment and low incomes. French disadvantaged district concentrates very high rates of social housing. Taking a threshold of 50% and more of social housing, Leboullenger et al. (2016) identified fifteen disadvantaged districts which are all located in the Grand Dijon. It is well established that the social status of a district impacts the household's residential choice. In the Grand Dijon, Baumont (2009) showed that the location in a Disadvantaged District and a location near a DD both impact negatively the housing prices.

Other accessibility variables are computed to measure the distance to the core of Dijon ($DistCBD$) and, for the house sample, the distance to the closest railway station ($DistRailSt$).[15] In each case, we use the Euclidian distance which is a good proxy of the road distance in the urban area of Dijon.

Finally we added a dummy variable $Year2014$ to control for the date of transaction. Table 3 summarizes the definitions and the sources of variables. Tables 4 and 5 show some descriptive statistics for the houses and apartments samples. The average price of a single house is 201 700 euros for an average surface area of 111 square meters and an average land area of 889 square meters. 50% of houses are situated at least 11.57 km away from the city center of Dijon and 2.8 km from a railway station. The average distance to a disadvantaged district is 10.8 km with a strong dispersion (almost 90% of the mean value) due to the distribution of houses throughout the urban area. In average, houses are

[12]Since 96% of the apartments in the sample have one bathroom (see Table 5), we do not include the variable $NbBath$ in the hedonic regression because of its multicollinearity with the intercept.

[13]See http://land.copernicus.eu/pan-european/corine-land-cover

[14]https://www.insee.fr/fr/statistiques/2410933

[15]Since apartments in the sample are concentrated in the center of the urban area, the Dijon train station, located in the core of Dijon, is the nearest railway station for almost all apartments. The $DistRailSt$ variable for apartments is then highly correlated with the $DistCBD$ one and was not taken into consideration.

4.19km away from blue amenities and 1.52km away from green ones.

The average price of an apartment is 116 500 euros for an average surface area of 58.14 square meters. Half of the apartments are closer than 1.7 km to the city center of Dijon and 2.06 km to a disadvantaged district. Apartments are close to either blue amenities or green amenities with respectively 2.8 km and 2.04 km as average distances and with smaller dispersions than for houses (s.d.$_{DistBlueAm}$= 1.18 and s.d.$_{DistGreenAm}$ = 0.8 respectively).

4 Spatial analysis

4.1 Neighborhood analysis and definition of spatial interaction patterns

The spatial weights matrix $W = w_{ij}$ is defined by the size of the neighborhood in which real estate transactions will be considered as dependent ($w_{ij} \neq 0$), and the strength of this dependence (value of w_{ij}).

Concerning the neighborhood, we apply here the definition based on the number k of nearest neighbors. Formally, observations i and j are considered as neighbors if $d_{ij} \leq d_{ik}$ where d_{ik} is the maximal distance such as the observation i has exactly k neighbors. Consequently, there is no isolated observation - *i.e.* without neighbors - in the spatial interaction patterns.

Thus the radius d_{ik} is specific to each observation i, it's probably smaller for denser areas than for dispersed ones: neighbors of isolated observations could be located at a greater distance, while for observations located in high density urban areas, nearest observations will be very close (see Figure 6). As the number k increases, the distance d_{ik} probably increases for each house i. When we assimilate this design of neighbors' set to the household behavior, it means that wherever the household is prospecting, a same amount of information is needed. This neighborhood definition seems to be well adapted to our study area and to houses and apartments markets.

Tables 7 and 6 show the distribution of distances between neighbors for the apartment and housing markets respectively. For increasing values of k, the distributions of quartiles as well as the mean values of distances are shown. The differences for the apartments and houses distributions are consistent with their respective spatial distributions (cf sec. 3.2). The apartments, concentrated in the center of the study area, are closer to each other: 75% of the apartments of the sample have their nearest neighbor located at 65 meters. 65 meters corresponds also to the mean distance between any two apartments in the sample. At least 25% of the apartments have their nearest neighbors in the same building. The houses are scattered on the urban area - about 2280 km^2 - thus they are more distant one from another with a potential of isolated houses. The choice of a k nearest neighbors W matrix avoids this problem. The mean distance between any two nearest houses in the sample is a little less than 400 meters, whereas 25% of the houses have their nearest neighbors located at 81,20 meters and 75% of them have their nearest neighbor at about 340 meters (cf Table 6 for k=1).

When k rises, the distances between neighbors increase on both markets (Table 6 and Table 7), but at a decreasing rate as k increases. The mean and median values of distances for the neighboring apartments distribution are lower than those for houses for every k. For the apartments, 75% of distances between k nearest neighbors are less than mean distances for every $k \geq 5$. This can be explained by the fact that some apartments are located far away from Dijon and its nearest suburb. Consequently, we have only kept the apartments located in the urban center and have deleted the few isolated observations, (see Figure 4) which shrinks our final sample to 1 423 apartments. For the houses, the mean distance is almost equal to the 3rd quartile value for 5 nearest neighbors, and the mean is less than the 3rd quartile for every $k \geq 5$; which confirms the dispersal of houses throughout the urban area. The final sample is unchanged.

To define the intensity of the neighbor relationship, one of the most common approaches used in hedonic evaluation is the distance based pattern for which the non-zero elements of the W matrix is a decreasing function of the distance between two neighbors.[16]

We use two specifications of w_{ij}:

- the inverse distance $w_{ij} = \frac{1}{d_{ij}}$. We name W_1 the corresponding matrix.
- the inverse squared distance $w_{ij} = \frac{1}{d_{ij}^2}$. We name W_2 the corresponding matrix.

Let us note that to compare the spatial analysis in the case of different matrices, we apply a row standardization, i.e. the spatial weights are transformed so that in each row the sum of the weights is equal to 1:[17]

$$\sum_{j=1}^{N} w_{ij} = 1.$$

4.2 Spatial autocorrelation of dwelling prices

When the distribution of a value (for example the prices per square meter of the apartments) and its geographical distribution coincides, one talks about spatial autocorrelation: prices per square meter are not randomly distributed upon an area. Positive (resp. negative) spatial autocorrelation will then result in the geographical grouping of similar (resp. different) values. To measure this global spatial autocorrelation, the Moran's I statistic (1948) is most frequently used, which is written as follows:

$$I = \frac{N}{S_0} \frac{\sum_i \sum_j (P_i - \bar{P}) w_{ij} (P_j - \bar{P})}{\sum_i (P_i - \bar{P})^2}, \tag{7}$$

[16] One can also consider a contiguity measure for which the interaction between each pair of neighbors is the same whatever the distance between them. Maslianskaïa-Pautrel and Baumont (2016) showed that this contiguity pattern does not represent faithfully the reality.

[17] The weights are now between 0 and 1, which allows comparisons of spatial parameters in different econometric models, and gives an interpretation in terms of the intensity of the neighboring links.

where P_i (resp. P_j) is the price per square meter of the dwelling i (resp. j), $\bar{P}$ is the mean price per square meter of all dwellings in the study, N is the number of observations (dwellings) and w_{ij} is the spatial weight corresponding to the dwellings i and j. S_0 is a scale factor equal to the sum of all elements of W. For a row standardizered matrix, $S_0 = N$.

We calculate the Moran's I values for apartment prices and for house prices for the two spatial matrices W_1 and W_2 (see Figures 7(a) and 7(b)) and for different values of k: from 2 to 150 nearest neighbors. For all configurations, the Moran's I test confirms the assumption of a positive spatial autocorrelation for the dwelling prices. We observe that the value of Moran's I statistic decreases with the increase of the number of nearest neighbors k: the larger neighborhood groups are, the greater the differences between prices. Indeed, to use weights inversely proportional to the distance (W_2 matrix) tends to rapidly reduce the importance of the values of the distant neighboring observations. Finally, the curve corresponding to house prices is systematically above the curve corresponding to apartment prices. This difference between the two curves confirms the idea that the house and apartment markets are two distinct markets and must be treated by two different empirical models (Palmquist, 2005). The results will then be presented separately, first for the houses, then for the apartments.

4.3 Spatial hedonic model selection

We apply the methodology developed by Maslianskaïa-Pautrel and Baumont (2016) in order to decide which spatial hedonic specifications are the most relevant and therefore to estimate adequately the implicit prices of the attributes (see Table 1). The analysis is implemented with four sets of neighbors $k = 5, 10, 15$ and 20 and two W matrices (W_1 and W_2). For the houses market and for the apartments one, a total of 12 spatial interactions patterns are tested for the specific-to-general and the general-to-specific approaches [18].

Results for the Specific-to-General approach

For houses, LM tests and their robust forms suggest the choice of the SAR specification for all spatial patterns. For apartments, these tests suggest the choice of SEM specification. The Common Factor test must then be carried out to determine whether the SEM or its extensive form (SDM) must be estimated. The results of the Common Factor test indicate the estimation of the SDM model.

Results for the General-to-specific approach

All LR tests confirm the choice of a general model versus a constrained model, for both houses and apartments, and for all spatial patterns, namely SDM or SDEM specification.

[18] Due to the lack of place, complete results are available upon request.

According to these conclusions, we choose to estimate the SDM hedonic specification. We recall that both SDM and SAR specifications imply a spatial multiplier effect on the estimated coefficients (Table 1), due to inverse spatial transformation $(I - \rho W)^{-1}$. It means that implicit prices associated with the attributes of the dwellings will then be amplified by diffusion effects through the characteristics of the dwellings of the study area. As pointed by Halleck Vega and Elhorst (2015), the spatial autoregressive model tends to force the spatial effect where the spatial Durbin model gives more flexibility. The SDM hedonic specification is then selected and estimated.

5 Results and discussions

This section presents the results of the estimates of SDM for apartments and houses using the spatial matrices W_1 and W_2. The specificities of each spatial distribution of houses and of apartments lead us to set $k = 5$ for the set of houses and $k = 10$ for the apartments and is relevant to the consumers' prospection behavior.

According to Maslianskaïa-Pautrel and Baumont (2016), the number of neighbors chosen in the specification may correspond to the information that housing seekers have access to. The cost of searching for information increases as the household looks at more and more housing ads. Sold houses are less concentrated than apartments (see Tables 7 and 6): consumer's prospection will be more difficult when looking for a house (k is then smaller) than for an apartment (k is larger).

For the two real estate markets and whatever the spatial matrix used, SDM estimates show a positive and significant value for the spatial parameter ρ for the two real estate markets and whatever the spatial matrix used. $\hat{\rho}$ is around 0.2 for the house market and is higher, around 0.26, for the apartment market. These results mean that a spatial diffusion process impacts the real estate values in the urban area of Dijon and that the diffusion process is higher in the urban center where the apartments are concentrated. It is then necessary to apply the spatial multiplier transformation $(I - \rho W)^{-1}$ to β et θ parameters to obtain the correct values of the implicit prices associated to all real estate attributes (see for exemple, Halleck Vega and Elhorst, 2015). Let us recall that the implicit prices estimated with the SDM is now a total effect which adds the direct effect and the indirect effect as explained in Table 1. In the case of the Spatial Durbin Model, the values of the estimated implicit prices may not be given neither by the estimated value of the β parameter only nor by the sum of the estimated values of β and θ[19].

Moreover, we have to underline that the results of SDM are different than the OLS ones. For the green value, specifically, OLS estimator clearly underestimates the effects of certification with the house's market. For instance, we find an elasticity price of -0.281 with OLS and -0.358 and -0.365 with SDM. For C, the result is insignificant for OLS but is significant with W2 (0.093). Concerning the apartments, we can observe, for example,

[19] Many differences on the values and their statistical significance can be observed when we compare the results of SDM estimations for the house market (Table 8) and for the apartment market (Table 10) to the total effects given in the Table 9 for the house market and Table 11 for the apartment market.

that the effect of being built after 1980 goes from 0.145 with OLS, to 0.224 for W1). These differences reminds us that space matters for econometric studies.

We now present the results for houses and then for apartments.

5.1 Houses

The values of the parameters given by the estimation of the SDM hedonic equation are shown in Table 8. The impact of multiplier effect are calculated and the resulting implicit prices of every characteristics are presented in Table 9.

Consistent with other studies, the elasticity for the living space is positive with a value around 1. The size of the land has a positive effect on housing price (around 0.13) which is inferior to the price of living space as expected.*Ceteris paribus* two or three-story houses are less expensive than one-story houses. The number of parking lots and the number of bathrooms have not any significant total effect on the price of a house.

The total effect of the variable *DistCBD* is significant negative and equals -0.26 which is consistent with the urban economic theory. The further from the central business district the household is located, the more housing prices have to decline to compensate for the rising costs of commuting. This result means that a 10%-increase of the distance from the CBD decreases the price of the house by 2.6%. For a house with the average price of 201 700 euros, located at the average distance of 13.48 km from the CBD, an increase of the distance of 1.3 km *ceteris paribus* decreases the price of the house by 5 244 euros.

The proximity to a train station has a positive total effect on house prices. The elasticity of this distance is equal to -0.03. This result shows that households are willing to pay for accessibility and mobility granted by train stations. The equipment rate per 1 000 inhabitants in the district has a positive and significant effect (around 0.017).

The proximity to a disadvantaged district has no significant effect on the house prices: the disadvanted districs are conentrated in the Urban Center and the houses are scattered on the urban area.

The implicit price of a house being built after 1980 is positive and significant (0.113 or 0.133 according to the type of W matrix). More “recent” houses are *ceteris paribus* more expensive than older ones by 12-14% or 24 204 - 28 238 euros for the average price of the house.

Ceteris paribus the prices of houses sold in 2014 ($Year2014 = 1$) are lower than in 2013: -9.7% (W_1 matrix) or -8.3% (W_2 matrix). This result, obtained both for houses and apartments, is consistent with a slowdown of dwelling prices observed in France since 2008 until 2015 due to the subprime crisis (INSEE, 2015).

Once we have indirectly controlled for the implementation of the French Thermal Regulations after the two oil shocks, the impacts for DPE labels are the followings. Concerning the green value associated with the Energy Performance Certificate, the ratings AB and C do not have any significant effect on its relative price with respect to the houses labeled D.

More precisely, a positive effect is observed for the DPE level C and for the spatial pattern W_2. *Ceteris paribus*, the difference of prices between a house labeled C and one labeled D is 9.75%, which corresponds to 19 665 euros for an average price house (201 700 euros). The energy savings are then valued by the buyers.

Eventually, we observe price depreciation for houses which have E, F or G ratings. Therefore, *ceteris paribus*, the implicit price of a house labeled F is lower than the implicit price of a house labeled D by - 0.18 which corresponds to a decreasing value of 16,5% and means a difference of 33 280 euros for an average-priced house. For the level G, the price is 30% lower which makes a 60 510 euros difference compared to an average-priced house labeled D. Less energy performed houses are then strongly depreciated by the real estate market.

5.2 *Apartments*

Estimated results are presented in Table 10 and the implicit prices of characteristics are given by the total effects in Table 11.

Concerning the living space, the elasticity is positive and equal to 0.8. *Ceteris paribus*, it means that an apartment 10% bigger will be 8% more expensive. If one considers an apartment with both an average living space of 58 square meters and an average price of 116 500 euros, it means that an apartment with a living space 6 m^2 bigger will be 9 320 euros more expensive.

The floor of the apartment has a non linear effect. The price of an apartment located at the 2nd or the 3rd floor is *ceteris paribus* higher than the price of an apartment on the ground floor: + 11.6% for apartment on the 2nd floor, and +7.3-8.3% for an apartment on the 3rd floor. The price of an apartment located at the 6th floor or more, is *ceteris paribus* 15.6% smaller than the price of an apartment on the ground floor. The location on other floors has not any significant effect with respect to an apartment on the ground floor.

The impacts of the number of parking lots ($NbPark$) are positive and significant. For one parking lot, the price is 14% higher than without any parking lot and for two parking lots, the price is 40.5% higher than without any parking lot.

The price elasticity of the distance to the center ($DistCBD$) is negative but less strong than this effect for houses: -11.3% for the matrix W_1 and -15.7% for the matrix W_2. This can be explained by the fact that apartments are much more spatially concentrated towards the city center of the urban area. Therefore, apartments are closer to the city-center with an easier access to transportation.

The price elasticity of the distance to the nearest disadvantaged districts ($DistDD$) is positive and significant (+0.08%): the closer from a disadvantaged district an apartment is, the lower its price. This result is consistent with the empirical literature focusing on the social status of deprived districts (Baumont, 2009; Baumont and Legros, 2013): people prefer living outside the deprived districts.

We estimate a positive and significant impact of the year of construction ($Post1980$). More precisely households are willing to pay more for an apartment in a building built after 1980: the implicit price is around 24% higher than for an apartment in a building built before 1980. This implicit price is higher than for houses because the apartment market is concentrated in the central area (the Grand Dijon) whereas the house market covers all the urban area. In addition, the real estate market for new apartment is small because available places for new buildings are scare in central cities and because once they have been bought they will be not resold before some time.

Like for the houses, the national trend observed in real estate market (INSEE, 2015) is also present for the apartment market in the Urban Center: the price of the apartments are 12%-13% lower in 2014 than in 2013.

The variable $Post1980$ indirectly controls for the implementation of the French Thermal Regulations after the two oil shocks. The additional impacts for DPE labels are the followings. We find no significant price for a green value brought by the apartments labeled AB or C compared to the DPE level D. In contrast, the apartment labeled E, F or G are negatively valued by the households.

The negative effects of labels E, F and G are going stronger for the lower level of energy efficiency. Therefore, *ceteris paribus*, the price of a label E apartment is lower than a D one by 6.8%, which does a difference of 7 922 euros for an average priced apartment. For an apartment labeled F, its price will be 8.6% lower than for a D one. For the mean price of an apartment, this difference counts for 1 019 euros. Finally, the price of an apartment with label G is 11.5% lower than with a D label. The worst level of energy performance depreciates the average price of the apartments by 13 398 euros.

6 Conclusion

Are energy savings capitalized into housing prices ? Do households agree to pay a higher price for energy-efficient dwellings ? In the urban area of Dijon, the green value of real estate is corroborated by our results: dwellings with a DPE lower than D are less valued. However, we observed that more performing housing (A, B or C) are slightly valued. Looking first at the negative effects, the Energy Performance Certificate reveals more easily the disadvantages associated with unfavorable labeling. In fact these bad levels may be associated with a poorer overall condition of the dwelling. Nevertheless, in a context where energy prices can increase, additional expenditures linked with low energy-performance certificates are likely to be considered by households. Concerning the performing levels, it should be noted that there aren't many energy-efficient dwellings on the market: respectively, houses and apartments with DPE A or B represent 1.1% and 1.4% of the market. Energy savings in modern housing may be not still enough concrete for households. Combining these two results implies that bad levels may act as additional incentives to improve the quality of older housings.

If the green value is highlighted, the overall environment must also be analyzed. The location of real estate is an important variable in the formation of real estate prices and shouldn't be ignored. Our analysis underlines this in two ways. First, at the level of neighborhood attributes and accessibility variables, a lot of effects are combined: negative as expected for the proximity to disadvantaged districts, negative as well for the distance to the Central Business District and positive for the proximity to green amenities. Environmental evaluation requires further study. Second, concerning the spatial diffusion mechanism, our results highlighted a spatial multiplier effect that impact housing prices all over the urban area: the real estate price in one location depends on the other real estate prices in other locations. Thus it could be interesting to study whether the behavior of households is influenced by their neighbors: for instance, do households living near an eco-district have a greater willingness to pay for energy-efficient housing than households living far from such district? If so, the rehabilitations of housing are fostered by geographic spillovers and public policies in favor of urban renovation should be developed in more districts. To investigate this question will be part of a future agenda.

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Table 1: Implicit price of housing attribute in different spatial models

Hedonic equation reduced form	Spatial process Variables (parameters)	Spatial effects Spatial dependence (Spatial spillovers)	Implicit price $(MWTP)^i_k$ of x^i_k $(= DE + IE)$	
			Direct effect, DE	Indirect effect, IE
OLS $P = \alpha I_N + X\beta + \epsilon$	None	None	$\hat{\beta}^i_k$	-
SLX $P = \alpha I_N + X\beta + WX\theta + \epsilon$	Explanatory (θ)	Modeled (local)	$\hat{\beta}^i_k$	$\hat{\theta}^i_k$
SEM $P = \alpha I_N + X\beta + u$ $u = \lambda W u + \epsilon$	Error (λ)	Un-modeled (nuisance)	$\hat{\beta}^i_k$	-
SDEM $P = \alpha I_N + X\beta + WX\theta + u$ $u = \lambda W u + \epsilon$	Explanatory (θ) and Error (λ)	Un-modeled (nuisance) and modeled (local)	$\hat{\beta}^i_k$	$\hat{\theta}^i_k$
SAR $P = \alpha I_N + \rho WP + X\beta + \epsilon$ $P = (I - \rho W)^{-1}(\alpha I_N + X\beta + \epsilon)$	Endogeneous (ρ)	Modeled (global)	Mean of diag.elements of $(I - \hat{\rho}W)^{-1}\hat{\beta}^i_k$	Mean of off-diag.elements of $(I - \hat{\rho}W)^{-1}\hat{\beta}^i_k$
SDM $P = \alpha I_N + \rho WP + X\beta + WX\theta + \epsilon$ $P = (I - \rho W)^{-1}(\alpha I_N + X\beta + WX\theta + \epsilon)$	Endogeneous (ρ) and Explanatory (θ)	Modeled (global and local)	Mean of diag.elements of $(I - \hat{\rho}W)^{-1}(\hat{\beta}^i_k + W\hat{\theta}^i_k)$	Mean of off-diag.elements of $(I - \hat{\rho}W)^{-1}(\hat{\beta}^i_k + W\hat{\theta}^i_k)$

Note: $\hat{\beta}^i_k$ and $\hat{\theta}^i_k$ denote the coefficients of the corresponding housing attribute x^i_k.

The nature of spatial dependence and spatial effects follows the taxonomy in Anselin (2003) and Halleck Vega and Elhorst (2015). First, we consider whether the spatial correlation in the reduced form pertains only to un-modeled effects (error terms), to modeled effects (included explanatory variables), or to both. Spatial autocorrelation is treated as a nuisance (error terms) or not (autoregressive). Second, we make the distinction between global and local spillovers. In the reduced form this comes down to the inclusion of a spatial multiplier effect coming from the spatial autoregressive process of endogenous variable (SAR) *versus* a simple spatial process coming from spatial lag of explanatory variables (SLX) .
Source: adapted from Maslianskaïa-Pautrel and Baumont (2016)

Table 2: Dwelling distributions according to *DPE* label

DPE	A	B	C	D	E	F	G	Total
Houses	0.25	0.84	12.25	30.37	27.94	16.44	12.08	100
Apartments	0.28	1.12	11.45	33.17	32.54	16.65	4.78	100

Note : The table shows the conditional frequency distributions of the *DEP* label for houses and for apartments. There are 1423 apartments and 1082 houses in the sample.
Data source: Notaries base PERVAL.

Table 3: Variable definitions

Variable	Description (Unit)	Source
ENDOGENOUS VARIABLE		
P	Price of the dwelling including taxes (euros)	PERVAL database
EXOGENOUS VARIABLES		
LivSp	Living space of the dwelling (m^2)	PERVAL database
NBBATH	Number of bathrooms in the dwelling (Discret variable with 4 modalities)	PERVAL database
NBPARK	Number of parking lots in the dwelling (Discret variable)	PERVAL database
LANDAREA	Lot area (m^2) - for houses only	PERVAL database
NBFLOOR	Number of study of the house (Discret variable with 4 modalities) - for houses only	PERVAL database
FLOOR	Floor of the apartment in the building (Discret variable with 7 modalities) - for apartments only	PERVAL database
DPE	Performance energy certificate - Discret variable with 6 modalities:	PERVAL database
AB		
C		
D	reference modality	
E		
F		
G		
Post1980	Binary variable, equal to 1 if the dwelling was built after 1980.	PERVAL database
EqRate	Ratio of the number of equipments in a district (*per* 1 000 *inhabitants*)	BPE database
DistCBD	Distance to the city-center of Dijon (km)	GIS calculated
DistRailSt	Distance to the closest train station (km)	GIS calculated
DistDD	Distance to the closest sensitive urban zone, “Disadvantaged District” (km).	Leboullenger et al. (2016) and GIS calculated
DistBlueAm	Distance to the closest “blue amenity” (km). Blue amenities are rivers and lakes	CORINE Land Cover and GIS calculated
DistGreenAm	Distance to the closest “green amenity” (km). Green amenities are parks and forests	CORINE Land Cover and GIS calculated
YEAR2014	Binary variable, equal to 1 if the transaction from 2014, 0 otherwise	PERVAL database

Table 4: Descriptive statistics for Houses sample

Continuous Variables

Variable	Min	Median	Mean (Std Deviation)	Max
P	15 500	187 000	201 700 (86 945)	750 000
LivSp	56	106	111 (29)	225
LandArea	27	610	889 (2 089)	57 280
EqRate	0	2.56	2.70 (2.88)	22.10
DistCBD	0.54	11.57	13.48 (10.19)	42.04
DistRailSt	0.095	2.8	4.3 (4.32)	24.26
DistDD	0.127	8.298	10.800 (9.474)	39.820
DistBlueAm	0.063	3.58	4.19 (3.27)	23.15
DistGreenAm	0.049	1.3	1.52 (0.807)	4.47

Discrete Variables

Variable	Number	%
NbBath		
1	777	71.81
2	275	25.41
3	28	2.58
4	2	0.18
NbPark		
0	217	20.06
1	733	67.74
2	119	10.99
3	10	0.92
4	3	0.28
NbFloor		
1	353	32.64
2	608	56.19
3	116	10.72
4	6	0.55
DPE		
AB	13	1.20
C	138	12.76
D	335	30.96
E	311	28.74
F	183	16.91
G	102	9.43
Year2014 (=1)	634	58.6%
Post1980 (=1)	368	34.01%

Sample size 1082 observations.

Table 5: Descriptive Statistics for Apartment Sample

Continuous Variables

Variable	Min	Median	Mean (Std Deviation)	Max
P	14 000	105 000	116 500 (59 183)	526 000
LivSp	18	59	58.14 (22)	157
EqRate	0	1.56	1.81 (1.85)	25.42
DistCBD	0.081	1.639	2.231 (2.126)	18.910
DistDD	0.062	2.063	2.011 (1.246)	17.000
DistBlueAm	0.327	2.8	2.8 (1.18)	8.54
DistGreenAm	0.08	2.11	2.04 (0.8)	3.8

Discrete Variables

Variable	Number	%
NbBath		
0	9	0.63
1	1365	95, 92
2	46	3.23
3	3	0.21
NbPark		
0	764	53.69
1	579	40.69
2	78	5.48
3	2	0.14
Floor		
0	317	22.28
1	363	25.51
2	308	21.64
3	220	15.46
4	101	7.10
5	42	2.95
6 and more	72	5.06
DPE		
AB	21	1.43
C	169	11.52
D	486	33.13
E	477	32.52
F	239	16.29
G	75	5.11
Year2014 (=1)	881	61.91%
Post1980 (=1)	433	30.43%

Sample size 1423 observations.

Table 6: Distance distribution for neighboring houses (k nearest neighbors)

k nearest neighbors	1^{st} Qu	Median	Mean	3^{rd} Qu	Max
1	81.20	167.05	393.63	335.28	7 799.17
5	205.37	386.19	921.34	1066.51	15 074.85
10	324.52	635.54	1433.37	2089.76	16 602.96
15	425.85	870.82	1825.98	2695.53	17 074.81
20	527.08	1082.88	2141.77	3146.10	18 414.79
25	618.82	1303.42	2417.02	3591.47	19 096.07
30	708.80	1506.25	2665.55	3962.15	19 837.01
35	796.16	1678.00	2889.93	4286.22	21 327.77
40	883.08	1861.90	3104.96	4577.37	21 491.18
45	962.09	2046.09	3312.15	4843.49	21 547.16
50	1034.55	2241.25	3509.43	5070.21	22 767.57

Sample size: 1082 observations. The minimum of distance between nearest neighbors is 2 meters.

Table 7: Distance distribution for neighboring appartements (k nearest neighbors)

k nearest neighbors	1^{st} Qu	Median	Mean	3^{rd} Qu	Max
1	0	21.34	65.53	65.29	9 004.62
5	6.01	84.37	145.43	140.45	9 119.03
10	75.84	129.82	228.62	209.06	9 481.45
15	102.33	165.85	289.53	266.42	15 591.23
20	122.56	196.12	337.26	307.59	15 605.21
25	141.25	225.11	376.79	345.73	15 624.81
30	158.27	251.44	412.25	383.54	15 646.63
35	173.71	273.71	446.83	421.46	15 656.12
40	187.90	294.49	479.75	456.33	15 701.61
45	202.87	314.25	510.45	488.74	15 726.60
50	217.28	333.17	539.10	520.04	15 732.05

Sample size: 1423 observations. The minimum of distance between nearest neighbors is 0 meters.

Table 8: SDM estimates for House Market

Coefficients	W_1 $\hat{\beta}$	W_1 $\hat{\theta}$	W_2 $\hat{\beta}$	W_2 $\hat{\theta}$
Intercept	5.753^{***} (0.554)		6.449^{***} (0.469)	
$LivSp$	0.602^{***} (0.049)	0.194^{*} (0.100)	0.617^{***} (0.049)	0.131^{**} (0.079)
$LandAr$	0.162^{***} (0.012)	-0.066^{***} (0.021)	0.161^{***} (0.012)	-0.052^{***} (0.017)
$NbFloor$ (1=Ref)				
2	-0.038^{**} (0.019)	-0.080^{**} (0.39)	-0.037^{*} (0.019)	-0.058^{*} (0.03)
3	-0.019 (0.030)	-0.103^{*} (0.061)	-0.019 (0.031)	$-0.073.$ (0.046)
4	0.107 (0.106)	0.235 (0.265)	0.104 (0.107)	0.069 (0.179)
$NbBath$ (1=Ref)				
2	-0.015 (0.533)	$-0.075.$ (0.051)	-0.016 (0.024)	-0.036 (0.038)
3	0.113^{**} (0.052)	-0.183 (0.133)	0.106^{**} (0.053)	-0.126 (0.101)
$NbPark$ (0=Ref)				
1	0.051^{**} (0.020)	-0.045 (0.044)	0.051^{**} (0.020)	-0.032 (0.033)
2	0.076^{**} (0.030)	-0.142^{**} (0.064)	0.079^{***} (0.031)	-0.096^{*} (0.049)
3	0.143^{*} (0.075)	0.002 (0.178)	0.146^{*} (0.075)	-0.226 (0.178)
$Post1980$	0.081^{***} (0.020)	0.021 (0.037)	0.080^{***} (0.020)	0.012 (0.029)
DPE (D=Ref)				
AB	0.003 (0.072)	0.180 (0.156)	0.005 (0.073)	0.064 (0.107)
C	0.014 (0.027)	0.060 (0.053)	0.014 (0.027)	0.062. (0.041)
E	-0.058^{***} (0.021)	-0.010 (0.042)	-0.057^{***} (0.021)	0.020 (0.032)
F	-0.145^{***} (0.025)	0.006 (0.052)	-0.147^{***} (0.025)	-0.003 (0.392)
G	-0.267^{***} (0.031)	-0.009 (0.066)	-0.272^{***} (0.032)	-0.027 (0.052)
$EqRate$	5.801 (5.738)	8.061 (8.228)	7.227 (5.894)	5.908 (7.483)
$DistCBD$	-0.093 (0.145)	-0.114 (0.148)	0.013 (0.175)	-0.226 (0.178)
$DistRailSt$	-0.032 (0.032)	0.011 (0.034)	-0.063 . (0.038)	0.039 (0.039)
$DistDD$	0.113 (0.081)	-0.130 . (0.084)	0.124 (0.101)	-0.141 (0.103)
$DistBlueAm$	0.016 (0.036)	-0.007 (0.039)	0.010 (0.044)	0.000 (0.045)
$DistGreenAm$	0.001 (0.029)	-0.041 (0.035)	-0.008 (0.031)	-0.024 (0.035)
$Year2014$	-0.043^{***} (0.015)	-0.036 (0.032)	-0.045^{***} (0.016)	-0.026 (0.025)
ρ	0.229^{***}		0.181^{***}	
Nb param	49		49	

Note: Number of observations 1 082.
Standard errors reported in parentheses. Statistically significance codes: *** - at 0.1%, ** - at 1%, * - at 5%, . - at 10%.

Table 9: The House Market: Spatial multiplier effects and Implicit prices (Total effect)

Coefficients	OLS	W_1 Direct Effect	W_1 Indirect Effect	W_1 Total Effect	W_2 Direct Effect	W_2 Indirect Effect	W_2 Total Effect
$LivSp$	0.656^{***}	0.621^{***}	0.413^{***}	1.033^{***}	0.634^{***}	0.279^{***}	0.913^{***}
$LandAr$	0.160^{***}	0.160^{***}	-0.036 .	0.124^{***}	0.159^{***}	-0.026	0.133^{***}
$NbFloor$ (1=Ref)							
2	-0.045^{*}	-0.043^{**}	-0.111^{**}	-0.153^{***}	-0.042^{**}	-0.074^{**}	-0.116^{***}
3	-0.036	-0.025	-0.133^{*}	-0.158^{*}	-0.025	-0.088^{*}	-0.113^{*}
4	0.115	0.121	0.323	0.444	0.107	0.100	0.207
$NbBath$ (1=Ref)							
2	-0.012	-0.019	-0.098	-0.117 .	-0.019	-0.044	-0.063
3	0.106.	0.104^{*}	-0.196	-0.091	0.099^{*}	-0.123	-0.025
$NbPark$ (0=Ref)							
1	0.049^{*}	0.049^{**}	-0.042	0.007	0.050^{**}	-0.026	0.024
2	0.077^{*}	0.070^{**}	-0.155^{*}	-0.085	0.073^{**}	-0.094 .	-0.020
3	0.140.	0.145^{**}	0.043	0.188	0.148	0.023	0.171
$Post1980$	0.104^{***}	0.084^{***}	0.049	0.133^{**}	0.082^{***}	0.075	0.113^{***}
DPE (D=Ref)							
AB	0.036	0.013	0.224	0.237	0.010	0.075	0.085
C	0.036	0.018	0.078	0.096	0.019	0.074^{*}	0.093^{*}
D	ref	ref	ref	ref	ref	ref	ref
E	-0.059^{**}	-0.058^{***}	-0.005	-0.062	-0.057^{***}	0.011	-0.046
F	-0.145^{***}	-0.146^{***}	-0.033	-0.180^{**}	-0.149^{***}	-0.034	-0.183^{***}
G	-0.281^{***}	-0.270^{***}	-0.087	-0.358^{**}	-0.277^{***}	-0.088	-0.365^{***}
$EqRate$	14.082^{***}	0.006	0.012	0.018^{**}	0.008	0.008	0.016^{**}
$DistCBD$	-0.242^{***}	-0.101	-0.168	-0.269^{***}	-0.003	-0.257	-0.260^{***}
$DistRailSt$	-0.035^{***}	-0.032	0.005	-0.027^{**}	-0.061 .	0.032	-0.029^{***}
$DistDD$	-0.029^{*}	0.107 .	-0.129^{*}	-0.022	0.116	-0.136	-0.021
$DistBlueAm$	0.021^{*}	0.016	-0.005	0.011	-0.010	0.002	0.012
$DistGreenAm$	-0.033^{*}	-0.001	-0.051	-0.052^{**}	-0.010	-0.030	-0.040^{**}
$Year2014$	-0.052^{**}	-0.046^{***}	-0.057 .	-0.102^{**}	-0.047^{**}	-0.040 .	-0.087^{**}

Note: Number of observations 1082.
Statistically significance codes: *** - at 0.1%, ** - at 1%, * - at 5%, . - at 10%.

Table 10: SDM estimates for the Apartment Market

	W_1		W_2	
Coefficients	$\hat{\beta}$	$\hat{\theta}$	$\hat{\beta}$	$\hat{\theta}$
Intercept	6.037*** (0.280)		6.373*** (0.270)	
LivSp	0.756*** (0.019)	−0.159*** (0.033)	0.756*** (0.019)	−0.133*** (0.030)
Floor (0=Ref)				
1	0.043** (0.019)	0.000 (0.029)	0.044** (0.020)	−0.006* (0.027)
2	0.058*** (0.021)	0.022 (0.031)	0.058*** (0.021)	0.024 (0.029)
3	0.001 (0.023)	0.057* (0.034)	0.002 (0.023)	0.048 . (0.031)
4	0.025 (0.029)	0.051 (0.044)	0.025 (0.030)	0.044 (0.040)
5	0.025 (0.042)	0.012 (0.070)	0.017 (0.042)	0.035. (0.064)
≥ 6	−0.046 (0.037)	−0.076 . (0.050)	−0.057 . (0.037)	−0.069 . (0.048)
NbPark (0=Ref)				
1	0.146*** (0.016)	−0.052** (0.024)	0.146*** (0.017)	−0.041* (0.022)
2	0.306*** (0.034)	−0.066 (0.051)	0.313*** (0.035)	−0.060 (0.046)
*Post*1980	0.086*** (0.020)	0.074*** (0.027)	0.086*** (0.021)	0.073*** (0.026)
DPE				
AB	0.109* (0.059)	−0.101 (0.091)	0.116* (0.060)	−0.099 (0.087)
C	0.051** (0.026)	−0.060* (0.034)	−0.050** (0.024)	−0.055* (0.031)
E	−0.035** (0.017)	−0.018 (0.025)	−0.036** (0.017)	−0.015 (0.023)
F	−0.072*** (0.022)	0.005 (0.032)	−0.072*** (0.022)	0.004 (0.030)
G	−0.085** (0.035)	0.18 (0.051)	−0.086** (0.036)	0.004 (0.046)
EqRate	13.107** (5.472)	−12.122 (6.833)	12.990** (5.704)	−11.385 . (6.950)
DistCBD	−0.147 (0.151)	0.060 (0.152)	−0.108 (0.162)	0.017 (0.163)
DistDD	0.122* (0.070)	−0.064 (0.071)	0.134* (0.075)	−0.075 (0.077)
DistBlueAm	0.088 (0.143)	−0.097 (0.145)	0.064 (0.152)	−0.068 (0.154)
DistGreenAm	−0.070 (0.075)	0.085 (0.078)	−0.059 (0.075)	0.073 (0.078)
*Year*2014	−0.047*** (0.014)	−0.051** (0.021)	−0.050*** (0.013)	−0.044** (0.019)
ρ	0.286***		0.248***	
Nb param	45		45	

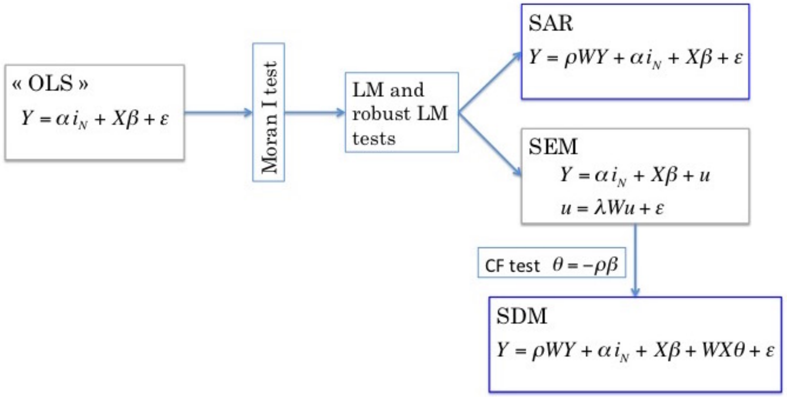
Note: Number of observations 1423.
Standard errors reported in parentheses. Statistically significance codes: *** - at 0.1%, ** - at 1%, * - at 5%, . - at 10%.

Table 11: The Apartment Market: Spatial multiplier effects and Implicit prices (Total effect)

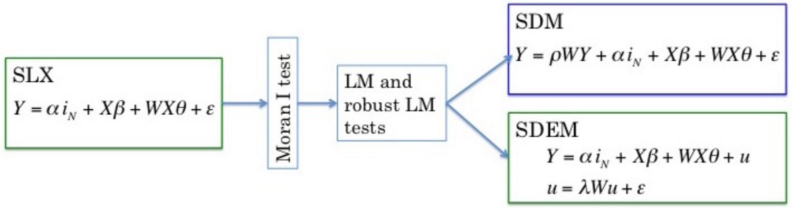
Coefficients	OLS	W_1 Direct Effect	W_1 Indirect Effect	W_1 Total Effect	W_2 Direct Effect	W_2 Indirect Effect	W_2 Total Effect
$LivSp$	0.786^{***}	0.763^{***}	0.073^{**}	0.837^{***}	0.762^{***}	0.065^{**}	0.828^{***}
$Floor$ (0=Ref)							
1	0.040.	0.045^{**}	0.016	0.061	0.045^{*}	0.006	0.051
2	0.058^{**}	0.062^{***}	0.050	0.112^{**}	0.063^{***}	0.047	0.109^{**}
3	-0.001	0.008	0.073 .	0.081 .	0.007	0.058 .	0.065
4	0.019	0.032	0.075	0.107	0.031	0.061	0.092
5	0.022	0.028	0.025	0.053	0.022	0.048	0.069
≥ 6	-0.107^{**}	-0.057 .	-0.114^{*}	-0.171^{*}	-0.067^{*}	-0.101^{*}	-0.168^{**}
$NbPark$ (0=Ref)							
1	0.017^{***}	0.144^{***}	-0.013	0.131^{***}	0.146^{***}	-0.006	0.140^{***}
2	0.317^{***}	0.309^{***}	0.028	0.337^{***}	0.315^{***}	0.021	0.336^{***}
$Post1980$	0.145^{***}	0.098^{***}	0.126^{***}	0.224^{***}	0.098^{***}	0.115^{***}	0.213^{***}
DPE							
AB	0.113.	0.101^{*}	-0.089	0.011	0.108^{*}	-0.085	0.022
C	0.035	0.046^{*}	-0.057	-0.012	0.045^{*}	-0.052	-0.007
D	ref	ref	ref	ref	ref	ref	ref
E	-0.038^{*}	-0.038^{**}	-0.036	-0.074^{*}	-0.039^{**}	-0.029	-0.068^{*}
F	-0.081^{***}	-0.074^{***}	-0.019	-0.093^{*}	-0.074^{***}	-0.016	-0.090^{**}
G	-0.096^{*}	-0.086^{**}	-0.008	-0.094	-0.088^{***}	-0.021	-0.109 .
$EqRate$	7.061.	12.096^{*}	-10.717	1.378	11.992^{*}	-9.857	2.134
$DistCBD$	-0.106^{***}	-0.145	0.023	-0.122^{***}	-0.122^{***}	-0.012	-0.171^{***}
$DistDD$	0.096^{***}	0.119^{*}	-0.037	0.081^{***}	0.129^{**}	-0.047	0.082^{***}
$DistBlueAm$	0.011	0.080	-0.091	-0.011	0.057	-0.063	-0.006
$DistGreenAm$	0.011	-0.062	0.083	0.021	-0.052	0.070	0.018
$Year2014$	-0.061^{***}	-0.056^{***}	-0.082^{***}	-0.138^{***}	-0.057^{***}	-0.067^{***}	-0.124^{***}

Note: Number of observations 1423.
Statistically significance codes: *** - at 0.1%, ** - at 1%, * - at 5%, . - at 10%.

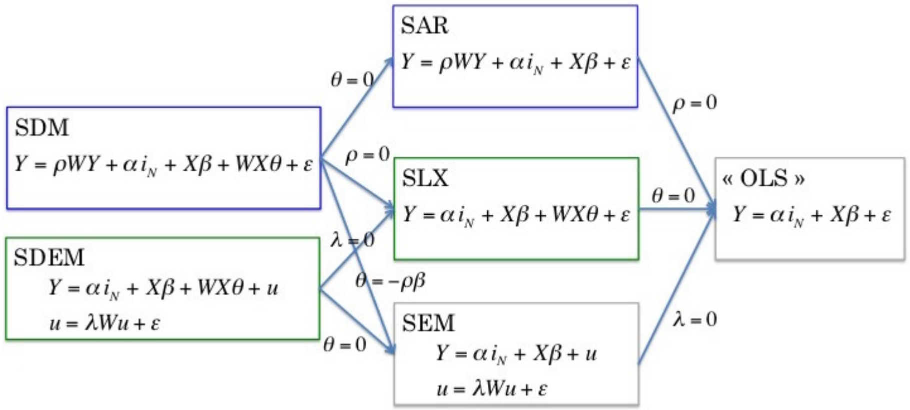
Figure 1: Spatial Model Selection



(a) Specific-to-General approach 1



(b) Specific-to-General approach 2

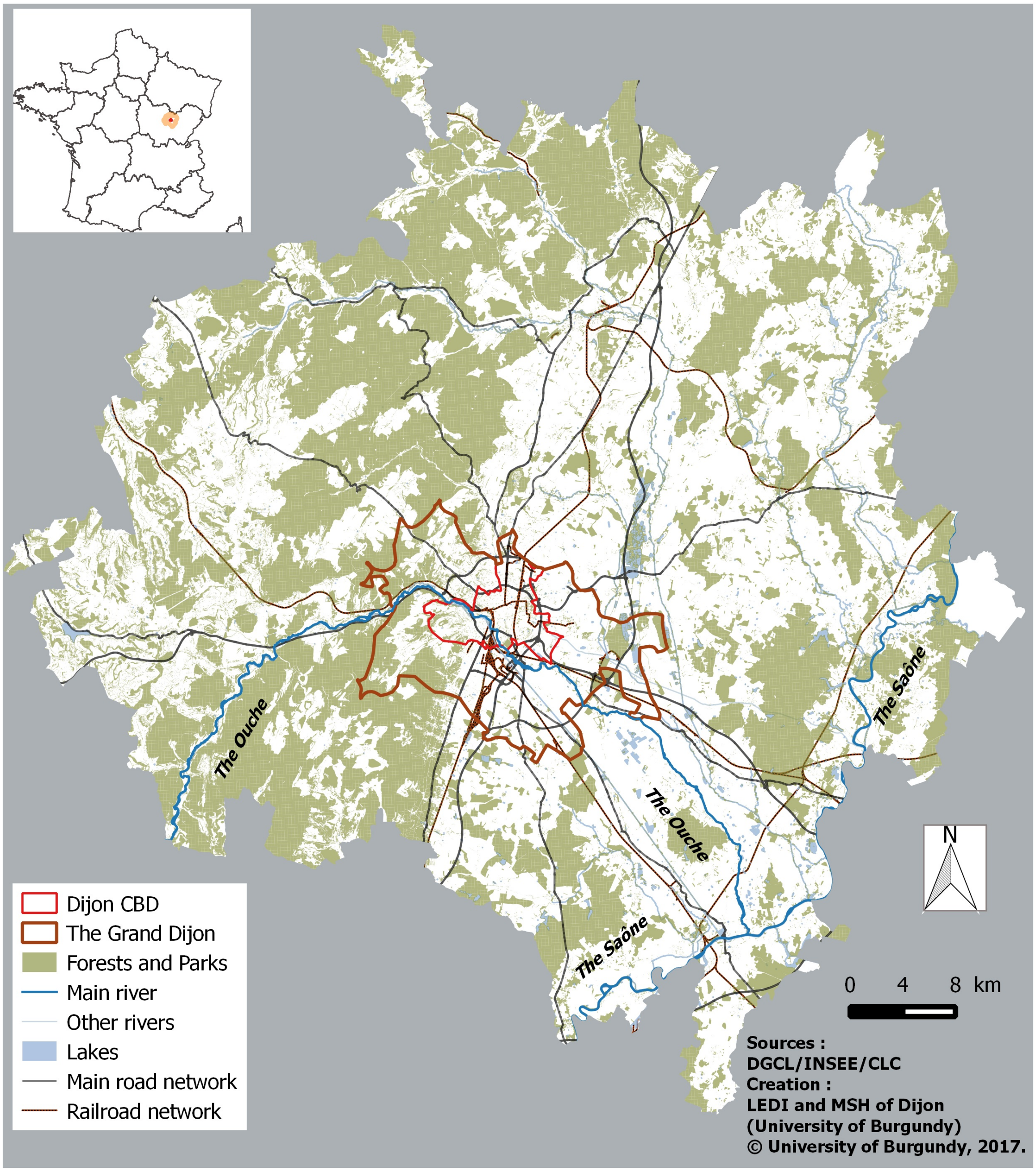


(c) General-to-Specific approach

$MWTP = \hat{\beta}$; $MWTP = DE + IE = \hat{\beta} + \hat{\theta}$; $MWTP = DE + IE = (I - \hat{\rho}W)^{-1} M_{ENV}(\hat{\beta}, \hat{\theta}, w_{ij})$.

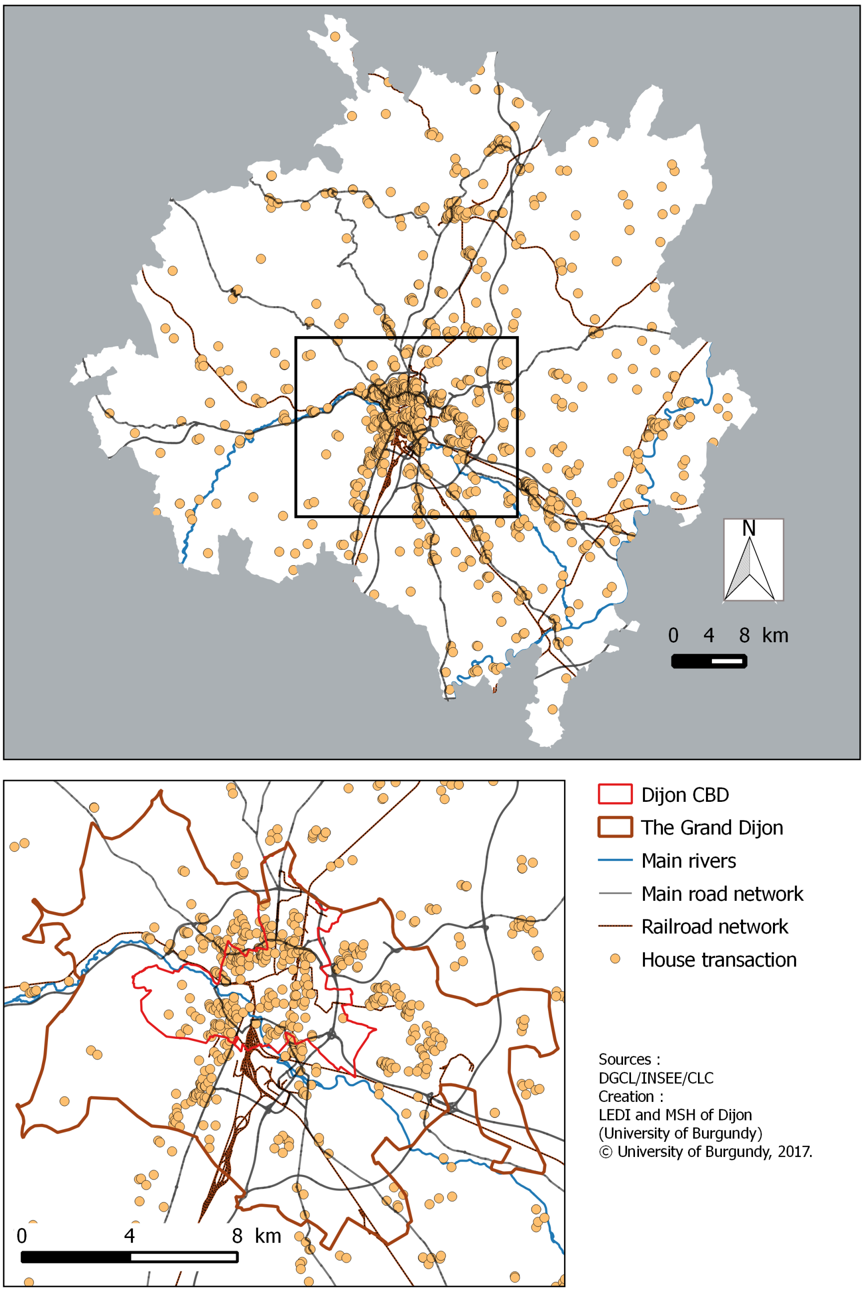
Source: Maslianskaïa-Pautrel and Baumont (2016)

Figure 2: Urbain area of Dijon



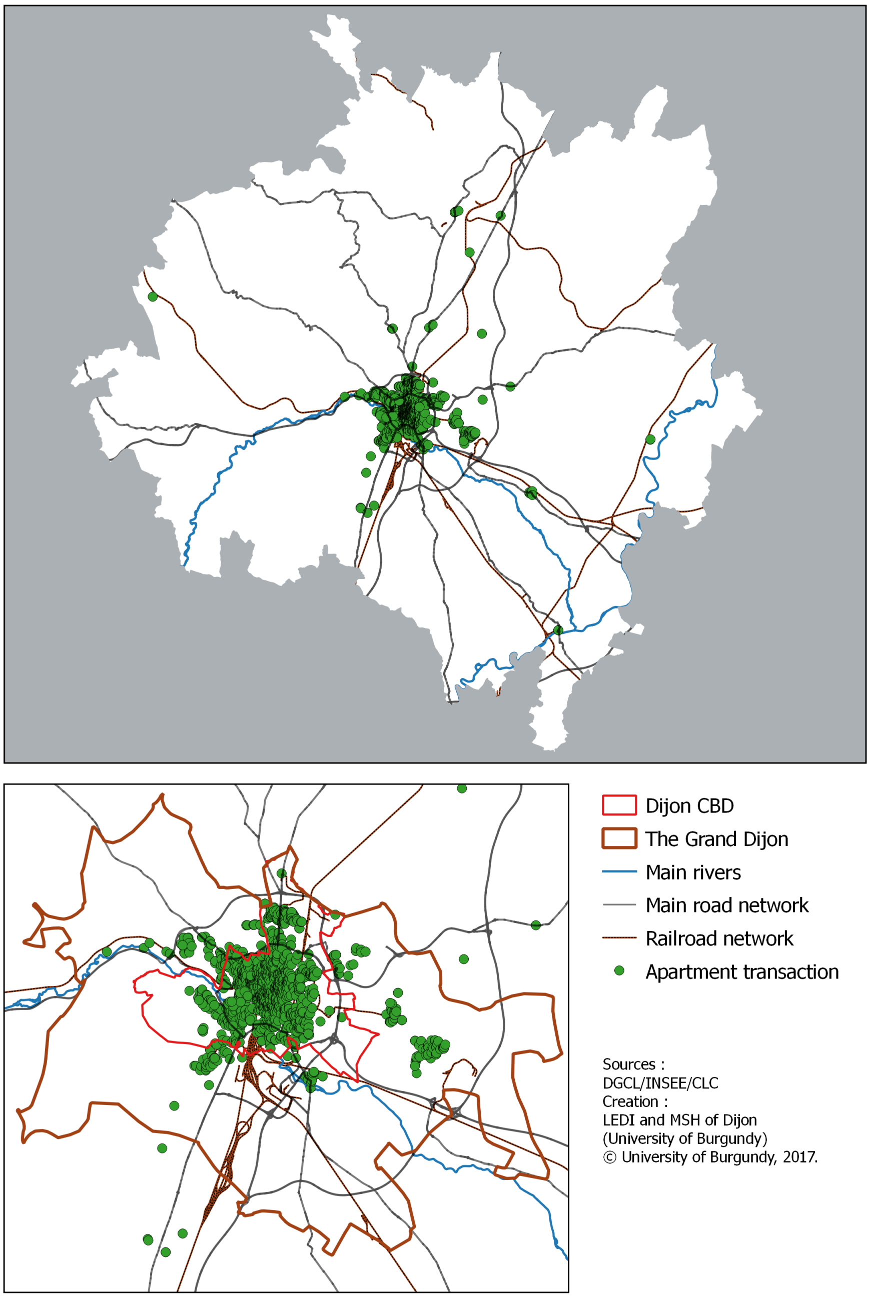
Creation: *LEDI and MSH of Dijon (University of Burgundy)*

Figure 3: Spatial distribution of Houses



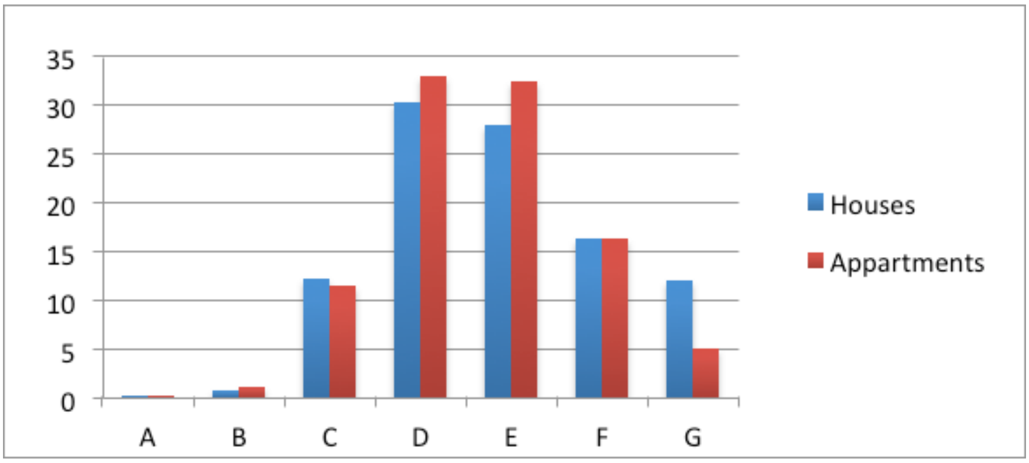
Creation: *LEDI and MSH of Dijon (University of Burgundy)*

Figure 4: Spatial distribution of Apartments



Creation: *LEDI and MSH of Dijon (University of Burgundy)*

Figure 5: Conditional distributions of DPE label for house and apartment markets



Note: The conditional frequencies in % are shown on the Y axis, the DPE categories on the X axis

Figure 6: Neighborhood of k-nearest neighbors ($k = 7$) in a dense area (a) and in a dispersed area (b)

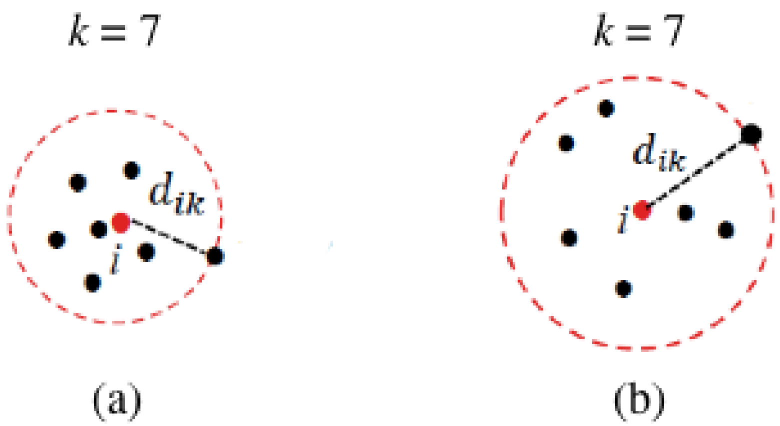
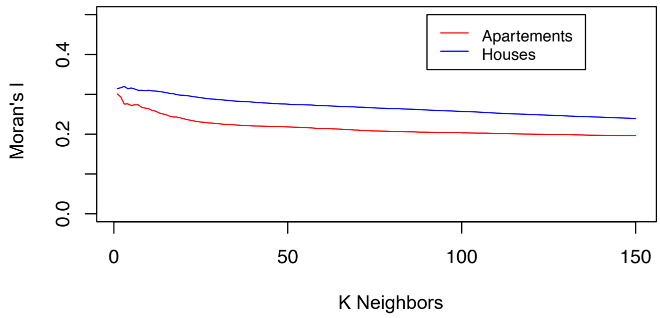
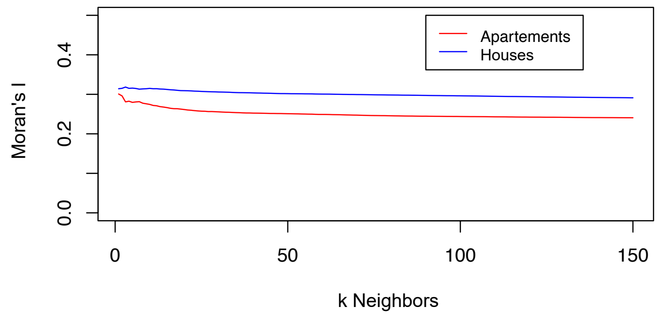


Figure 7: Spatial autocorrelation of housing prices



(a) W_1 spatial weight matrix (inverse distance).



(b) W_2 spatial weight matrix (inverse distance).

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