13, allée François Mitterrand
BP 13633
49100 ANGERS Cedex 01
Tél. : +33 (0) 2 41 96 21 06

Web : http://www.univ-angers.fr/granem

Granem
Groupe de Recherche ANgevin en Economie et Management
UMR-MA n°49

The nature and impacts of environmental spillovers on housing prices: A spatial hedonic analysis

Masha Maslianskaia-Pautrel
GRANEM, Université d'Angers

Catherine Baumont
LEDi, Université de Bourgogne et CNRS

février 2015

Document de travail du GRANEM n° 2015-01-044

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Classification JEL : Q51, C21, C18

Mots-clés : évaluation environnementale, modèles hédoniques spatiaux, effets direct et indirect, matrice de pondérations spatiales, spillovers.
Keywords: direct and indirect effects, environmental valuation, spatial hedonic models, spatial weight matrix, spillovers.

Résumé : L'article s'intéresse à la dimension spatiale des effets environnementaux. Nous utilisons des avancées récentes de l'économétrie spatiale pour montrer que l'interprétation des estimations hédoniques en tant que prix implicite des attributs des logements dépend de la spécification du modèle spatiale. Notamment, le prix implicite combine un effet feedback et un effet de propagation et peut être interprété en termes de spillovers locaux et globaux. Nous construisons un modèle empirique de l'espace estuarien ligérien, un espace rural et urbanisé avec des zones naturelles et des espaces plus artificialisés. Nous étudions différents schémas d'interaction spatiale pour tester la robustesse de nos estimations. Cette analyse suggère que les schémas basés sur la distance inverse et de petits voisinages aboutissent à des estimations stables. Ce résultat est également cohérent avec un comportement des ménages qui s'intéressent dans leur recherche à la comparaison avec des maisons plus proches et limitent les zones d'investigation. Comme attendu, l'impact positif est concentré sur les attributs traditionnels comme la proximité au front de mer et les endroits calmes. Au contraire, la présence de zones humides de différents types a un impact négatif probablement à cause de risques (d'inondation et d'autres) associé avec cette proximité. En outre, si les quartiers urbanisés sont plus appréciés par les ménages, c'est plutôt parce que les zones rurales le sont moins que pour les aménités urbaines elles-mêmes.

Abstract: This paper investigates the spatial dimension of the environmental effects. We use recent advances in spatial econometrics to show that hedonic equations produce estimates to be differently interpreted as implicit prices according to spatial models. In particularly, the implicit price of housing attribute combines a feedback effect and a propagation effect and may be interpreted in terms of local or global spillovers. We drive an empirical study in the estuary of the Loire, a rural and urban area well occupied by various natural areas and more artificialized ones. We study various spatial interaction patterns to test the robustness of our estimates and we find that spatial dependencies based on inverse distance and small neighborhoods provide stable estimations. It is consistent too with realistic spatial interaction patterns for household behaviors: information on closer housings is more reliable and comparison areas are in fact limited by the research process. As expected, positive impacts are concentrated on traditional attributes like the proximity to the ocean frontage and quiet places. On the contrary, the presence of various natural wet amenities is negatively valued because of the impression of housing density associated to flood risk. If urban places are more valued by households, it's rather because rural location are less desired than because of urban intrinsic attributes.

Masha Maslianskaia-Pautrel
Faculté de Droit, Economie et Gestion
Université d'Angers
masha.pautrel@univ-angers.fr

Catherine Baumont
Laboratoire d'Economie de Dijon
Université de Bourgogne
Catherine.baumont@u-bourgogne.fr

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Masha Maslianskaia-Pautrel*, Catherine Baumont†

February 1, 2015

Abstract

This paper investigates the spatial dimension of the environmental effects. We use recent advances in spatial econometrics to show that hedonic equations produce estimates to be differently interpreted as implicit prices according to spatial models. In particularly, the implicit price of housing attribute combines a feedback effect and a propagation effect and may be interpreted in terms of local or global spillovers. We drive an empirical study in the estuary of the Loire, a rural and urban area well occupied by various natural areas and more artificialized ones. We study various spatial interaction patterns to test the robustness of our estimates and we find that spatial dependencies based on inverse distance and small neighborhoods provide stable estimations. It is consistent too with realistic spatial interaction patterns for household behaviors: information on closer housings is more reliable and comparison areas are in fact limited by the research process. As expected, positive impacts are concentrated on traditional attributes like the proximity to the ocean frontage and quiet places. On the contrary, the presence of various natural wet amenities is negatively valued because of the impression of housing density associated to flood risk. If urban places are more valued by households, it's rather because rural location are less desired than because of urban intrinsic attributes.

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Introduction

With growing awareness for environmental issues at urban level, well-being in cities and good environmental local policies will increasingly drive household location decisions and

*Corresponding author: masha.pautrel@univ-angers.fr, GRANEM, University of Angers.

†catherine.baumont@u-bourgogne.fr, Laboratoire d'Economie de Dijon (LEDi), University of Bourgogne and CNRS UMR 6307.

political agendas. Hedonic evaluation provides an interesting method to estimate the links between a large set of factors likely to affect housing market and consumers' behaviors. Hedonic housing model is widely used in environmental evaluation too, and is applied to various contexts, such as the demand for air quality (Brasington and Hite, 2005; Neill et al., 2007; Yusuf and Resosudarmo, 2009) or ecosystem services (Ma and Swinton, 2011), the impact of airport or trafic noise (Day et al., 2007; Cohen and Coughlin, 2008), of hazardous waste sites (Boxall et al., 2005), the effects of water quality (Leggett and Bockstael, 2000; Poor et al., 2007; Cho et al., 2011) or of food risk (Daniel et al., 2009), as well as the valuation of environmental amenities such as landscape, view, and beach quality (Cavailhes, 2009; Landry and Hindsley, 2011).

Spatial data and spatial factor such as location, accessibility, concentration and spillovers inherently define environmental variables, housing choices and planning policies. It brings a lot of well-known problems in estimation techniques and many empirical studies - in particular among above mentioned - are worrying about them and use spatial econometric tools to define and estimate spatial hedonic specifications. It has been proved that considering spatial dependencies is better than ignoring them (Dubin, 1992; Pace and Gilley, 1997) and improves estimations and previsions in hedonic housing models (Basu and Thibodeau, 1998; Beron et al., 2004; Wilhelmsson, 2002). Therefore, as noted by Kuminoff et al. (2010), the "*widespread use of the hedonic model for policy evaluation makes it especially important to understand the method's strengths and limitations.*"

The present paper contributes to this understanding and aims at improving the spatial hedonic environmental evaluation in three directions.

One point is to better understanding the spatial dimension of environmental impacts which does not reduce to spatial measures and spatial externalities but involves the spatial organization of environmental attributes as a whole. We suggest referring to the concept of anthropization to focus on this spatial dimension. In fact, one spatial organization of attributes - either environmental or not - observed at one time reflects many transformations induced by human actions, human behaviors and planning or public policies whose results have changed the attributes of economic space belonging to three sets commonly included in hedonic models: housing attributes, neighborhood attributes and accessibility attributes. The spatial dimension means that once these changes have been individually taken into account and estimated, an additional impact corresponding to the global spatial pattern might remain: : it combines more precisely direct - or feedback - effects and indirect - or propagation - effects.

Second, recent advances in spatial econometric tools (Elhorst, 2010; LeSage and Pace, 2009; Vega and Elhorst, 2013) showed that hedonic equations, even modeling the spatial dimension, produce estimates to be differently interpreted according the econometric specification and the nature of the spatial autoregressive term. In many cases, to estimate the coefficients of the explanatory variables is not enough for environmental evaluation. An accurate algebraic transformation should be needed once these coefficients have been estimated. The spatial dimension of environmental evaluation will then potentially be described in terms of local and global spillovers.

The third point is about the spatial weight matrix which defines the spatial organization in the case study - i.e. interactions between each localized observation within the space. In fact, the choice of a spatial weight matrix is not neutral: it has to be made to correspond at best with the true data generating process (Bhattacharjee and Jensen-Butler, 2006) or to be a good complement to spatial explanatory variables like neighborhood or accessibility variables (Wilhelmsson, 2002). In some cases, especially with microlevel data and large number of observations (Bell and Bockstael, 2000), the choice of spatial weights has potentially impacts on the estimates because it affects the choice of the spatial specification to estimate and then command to calculate the global impact of the attribute with the accurate method.

Since the choice of appropriate spatial specification and spatial weight matrix appear as dependent, to test their robustness will be driven in our paper as follows. For the identification of specification we implement two approaches: "*General-to-Specific*" and "*Specific-to-General*" briefly described, in the former case, as starting with a most generic model and test it against more specific ones, or vice versa in the latter case. Statistical tests depending on the spatial weight matrix, we define various spatial patterns and compare the results especially for the estimation of implicit prices - i.e. impacts, associated to environmental variables.

To this end we undertake an empirical investigation for the region of the lower Loire estuary (France), hereafter named *Basse-Loire*, using an original database on real estate transactions from which 1989 single family houses sold between 2004 and 2006 have been extracted. The empirical analysis illustrates how the information on housing, capitalized in the entire spatial distribution of housing transactions, may improve the implicit price estimates, especially for environmental attributes. For example, larger prices for single family houses located close to the ocean frontage are enhanced above all by larger prices of neighboring houses and don't depend on pure seaboard amenities. Moreover, when spatial effects are ignored, some environmental effects are ignored too: for example, being located close to some noisy roads is not significant in that case but is significant and positive once spatial effects are included. In fact, the resulting effect combines two significant effects, a negative effect (noise) but a stronger positive one (accessibility). Finally, spatial dependence patterns allowing to capture local information and to control for heterogeneous spatial distribution of attributes provide stable estimations. It is consistent too with realistic spatial interaction patterns - inverse distance and small neighborhoods - for household behaviors: information on closer housings is more reliable and comparison areas are in fact limited by the research process.

The remainder of the paper is organized as follows. In the first section, we discuss the nature of environmental attributes and spatial spillovers to be valued by hedonic methods. Section 2 presents the spatial econometrics issues in environmental hedonic models. The case study is reviewed in the third section and the fourth section outlines the empirical strategy. Section 5 details results and interpretations for environmental evaluation. Some concluding remarks complete the paper.

1 Environmental spillovers in anthropized areas.

Environmental evaluation by hedonic model estimations of housing prices are known as relevant and well developed in empirical literature. As spatial analysis of housing price became a standard in the last decades, environmental evaluation should question its common features and its improvement margins in this framework. First, we establish a parallel between each category of hedonic characteristics and environmental characteristics and we clarify the dimension of environmental externalities. Then we go in depth with the spatial dimension of environmental evaluation and suggest to refer to the concept of anthropization to describe it.[1]

1.1 Categorization of environmental characteristics for housing choice

According to urban microeconomic models, the housing choice maximizes the residential utility depending on intrinsic characteristics of the house and extrinsic (i.e. relative) characteristics which are associated to its location. The corresponding hedonic equation defines housing prices P as a function of three bundles of characteristics (Baumont, 2009):

$$\mathrm{P} = f(H; N; A) \tag{1}$$

The first one, H, is composed of structural - i.e. intrinsic- attributes describing the physical characteristics of housing and satisfying household preference for residential services (Muth, 1969). The second one, N, includes neighborhood variables depicting the quality of amenities and the economic and social characteristics in the neighborhood of the house. We can speak of local extrinsic attributes revealing the identification preference of the household (i.e. the type of society where he wants to live). The third bundle, A, is composed of accessibility variables including distances to major places of employment, to major amenities (leisure, shopping and public facilities, outstanding sites, etc.), and to road infrastructures or transport access points (train stations, subway stations, major streets, highways, airports, etc.). We speak of global extrinsic attributes i.e. within the entire territory - satisfying household preferences for markets integration (Bajari and Kahn, 2005).

All these categories are concerned by environmental attributes. Building materials and heating system for example impact directly on the environmental services of housing whereas the housing size, the number of floors, the age of building... are indirect indicators. Neighborhood environmental variables indicate the quality of environmental amenities in the surroundings such as air quality, sound nuisance, open space, scenic views, biodiversity ... among many others and as far as measures are available. Finally a large set of accessibility variables measuring the distance to environmental amenities (or disamenities) may be introduced in hedonic equations: distance to industrial center, distance to a river, distance to the sea, distance to airports, distance to natural reserve or green belt...

These examples underline how environmental conditions may be omnipresent in residential choices both in direct forms and implicit ones which requires various variables and data. Environmental evaluation, as a recent concern, is all the more complicated by unavailable data and measurement problems. However, hedonic evaluation appears as a convenient method to assess the impact of environmental variables on housing prices under the commonly assumption that environmental amenities or disamenities are capitalized in housing prices. Implicit prices and environmental externalities may then be assimilated.

By extension, neighborhood and accessibility variables are interesting proxies to capture the spatial dimension of environmental externalities characterizing many environmental goods or services: scenic view, landscape, air, water or ground pollution, noise, smell and waste management... Neighborhood variables capture a localized dimension of environmental externalities: they only impact surrounding housing and the impact changes from a neighborhood to another one. For example, the percentage of green space in a neighborhood generally differs from a neighborhood to another one even for adjacent districts. On the contrary, modeling accessibility variables refers to a more global dimension of spatial externality potentially affecting all housing of the sample, as for air or sound pollution for example. The impacts are generally decreasing as distance to the emission source increases and many specifications or functional forms based on distance may be used to fit the best impact of each environmental variable: euclidian distance for scenic view, inverse distance squared for sound nuisance... Of course, the way a specific environmental variable is of neighborhood type or accessibility type is not given and may vary in empirical studies. For example, the impact of a scenic view (or of an airport) concerns a restricted area if we consider the absolute rent a household is (or not) willing to pay for. It concerns all housing within the studied area if it is the marginal rent a household is willing to pay to be closer (or further). Data availability may guide the empirical choice too: sound nuisance propagates everywhere but it is easier, and better, to consider a zoning map displaying neighborhoods either spared or impacted by sound nuisance. In the same way, it is somehow assumed that environmental externalities may be neglected beyond a distance threshold from the emission source (for example, sound nuisance may be neglected beyond a distance of 500 meters).

1.2 Spatial dimension and anthropization in environmental hedonic evaluation

In fact, neighborhood variables or accessibility variables and spatial externalities as well help describing the spatial dimension of environmental characteristics in terms of localization and patterns of propagation from these locations. For that, they are an integral part of what we name the spatial dimension of environmental evaluation but don't entirely make it up.

The spatial dimension of environmental evaluation means that spatial organization and spatial dependence patterns account in estimates: many things, if not all things, are not randomly distributed within spaces and according to the first law of geography "*near things are more related than distant things*" (Tobler, 1970, p. 236). In recent decades, more and more empirical studies take care of spatial dependencies in environmental hedonic evaluation and it is now a well established evidence that housing prices are spatially dependent. In fact, similar housing prices are more often observed in nearby location than if they were spatially randomly distributed but we can also observe clusters of high values in some districts and cluster of low values in other districts. These examples refer to the two basic forms of spatial dependencies (Anselin, 1988): spatial autocorrelation in the first case and spatial heterogeneity in the second one.

To take care of spatial dependencies implies that we have to take care of three mechanisms: the spatial distribution of housing values, the spatial distribution of their explanatory factors and the spatial interactions within and between these location patterns. In other words, not only locations matter but interactions between locations matter too (Baumont and Legros, 2013).

To clarify the interactions between spatial patterns and environmental evaluation, we suggest to refer to the idea of *anthropization.* In geography and ecology, the term anthropization refers to the transformation of natural space under the effect of human actions. Every space may then be described as more or less anthropized from totally wild to entirely transformed. The degree of anthropization is defined by the same bundle of environment characteristics as before (air pollution, noise, landscape, biodiversity, ecosystems...) but considered as built by human behaviors and some developing and planning actions, either public or private.

Environmental variables produce spatial dependence in housing prices for at least four reasons. First, housing prices tend to be spatially autocorrelated according to similar intrinsic and extrinsic attributes. In fact, at each period of residential development, buildings located in the same development area tend to have the same intrinsic characteristics in terms of residential services and especially environmental properties related for example to thermic or acoustic insulation. Real estate properties belonging to the same neighborhood share the same environmental amenities and finally accessibility variables and spatial externalities tend to equally impact all equidistant housing. Second, many public policies have deeply shaped the environmental allocations of rural and urban spaces through planning policies, zoning policies or preservation policies. Some public policies raise the environmental allocations in some sites by creating, protecting, developing or renovating green belts, landscapes, natural resources or natural sites whereas other public policies are, on the contrary, responsible for environmental degradations in other sites: traffic congestion, industrial nuisances, natural space destructions... Once again, the spatial distribution of housing prices exhibits spatial autocorrelation for similar sites and spatial heterogeneity across different sites. Third, many private operators (real estate agents, property developers, builders...) and public tax offices, actually evaluate housing prices in response to the prices observed at neighboring locations which self-reinforces the spatial autocorrelation process in housing prices. Fourth and finally, increasing diffusion of knowledge on sustainable development makes more and more households aware of “environmental living standard” which strenghens the diffusion of environmental preferences across consumers.

For all these reasons, the anthropization processes build the location patterns of environmental allocations and support important sources of spatial dependencies across housing prices. Controlling for spatial dependencies by introducing environmental variables in hedonic models must not be ignored.

In addition spatial dependencies underline the role played by the spatial organization of prices and their explanatory factors. The price of one real estate property is not only affected by its own environmental attributes but it is potentially affected by the entire spatial distribution of environmental attributes all over the space. Then, once the impact of an environmental attribute on the price of a real estate property has been estimated, two questions follow. How does the impact of one price spread to other prices? How does one evaluate the global effect of each environmental attribute i.e. the effect of the spatial distribution of each environmental attribute? The underlying processes appeal to several but jointly mechanisms known as endogenous amenities, neighborhood effects and neighborhood dynamics which could not be dissociated in the household's residential choice (Ioannides and Zabel, 2008). A neighborhood effect means that the household gains (or looses) from social interactions with his neighbors (Manski, 2000; Durlauf, 2004). Assuming endogenous amenities means that the household prefers living closer to households with similar socio-economic status (Brueckner and Rosenthal, 2009; Tivadar, 2010). Finally neighborhood dynamics means that households preferences tend to gradually diffuse across neighborhoods because neighborhoods are not "*isolated islands*" but are overlapped neighborhoods (Strange, 1992; Aaronson, 2001). Since choosing a real property encompasses a location choice and a neighborhood choice, then people tend to have similar preferences for amenities and socio-economics status: housing prices tend to be spatially autocorrelated within the neighborhoods. Since these properties gradually diffuse across neighborhoods, people demand for environmental amenities and social-economic amenities tend to gradually diffuse across neighborhoods too. Housing prices within a neighborhood and in closer neighborhood tend to be similar as far as the diffusion processes do not stop because of some barriers such as natural barriers or communication routes barriers (peripheral roads, railways...). Anthropization process gradually spreads over the space giving it its urbanized changes and environmental features.

Finally, the spatial dimension of environmental evaluation brings out the potential role played by a fourth set of attributes: the effect of the spatial organization - i.e. spatial dependencies - of attributes explaining housing prices. Recent spatial analysis literature (Elhorst, 2010; LeSage and Pace, 2009; Vega and Elhorst, 2013) shows that ignoring this dimension leads to wrong interpretations of estimates in econometric specifications. To our knowledge, this problem has not been considered yet in environmental hedonic model even if spatial hedonic models have been used.

2 Estimation of spillovers in spatial hedonic model

Taking care of spatial dependencies in environmental evaluation means that adequate estimating methods should be implemented and adequate spatial interpretation of estimations should be made.

2.1 Hedonic model techniques

The hedonic property value model is based on the seminal work proposed by Rosen (1974), according to which the equilibrium on the housing market can be used to assess willingness-to-pay (or at least marginal willingness-to-pay) for non-market-tradable changes in environmental externalities. Rosen's model demonstrates that the functional relationship between the price of a differentiated product (dwelling) and its attributes can be interpreted to be an equilibrium outcome of the interactions between all the buyers and sellers in a market. This functional relationship is called the hedonic price function. Under the assumptions of the model, regressing housing prices on their attributes can reveal consumers' marginal willingness-to-pay (MWTP) for individual attributes of a differentiated product, such as the environmental characteristics of a house:

$$P_i = f(x_i^1, ..., x_i^{env}, ..., x_i^k) + \epsilon_i, \quad \rightarrow \quad MWTP_i = \frac{\partial P_i}{\partial x_i^{env}} \qquad (2)$$

where P_i is the price of the house i and $X = (x_i^1, ..., x_i^{env}, ..., x_i^k)$ is a matrix of housing attributes as described in equation (1). The MWTP obtained from the hedonic regression is then used on the second stage of the estimation procedure, to recover the demand for environmental amenity:

$$MWTP_i = g(x_i^1, ..., x_i^{env}, z_i^1, ..., z_i^m) + u_i \rightarrow P_{env} = h(x^{env}) \tag{3}$$

where $(z_i^1, ..., z_i^m)$ is a vector of buyer characteristics.

The question of the robustness of the MWTP estimate is of crucial importance because it is used as endogenous variable in the environmental demand regression (second stage). Two points are especially important in empirical hedonic studies with respect to the MWTP calculation. First, the functional form of the hedonic price function is not defined theoretically. Second, when spatial econometric methods are used to account for spatial dependencies, it leads to additional problems of model specification.

Theoretically, the form of the hedonic price function depends on the preferences of buyers and sellers. In most cases, however, it is nonlinear and has no closed-form solution. Ekeland et al. (2004) show that such a nonlinearity is a generic characteristic of the hedonic price function, and is necessary to identify the individual demand for an attribute. In their analysis of different functional forms of the hedonic price function, Cropper et al. (1988) suggest the use of simpler functional forms (linear, log-linear, log-log, and linear Box-Cox) in the presence of the omitted variable. However, they fail to recommend the use of any one functional form in particular.

The choice of functional form affects the MWTP for a given environmental (or other) housing attribute. Indeed, when the hedonic function is linear, the MWTP is equal to the estimated parameter of the corresponding environmental variable. For a non-linear functional form, the MWTP becomes a function of the environmental variables and therefore depends on observations (MWTP for a house i depends on attributes of this house).[2]

In addition, in spatial hedonic regression, according to the spatial specification the implicit price could depend on the value of environmental variables for neighboring observations or for all observations in the sample. In this case our interest concerns the value of the effects of environmental variables more than the value of the coefficient estimate.

2.2 *Implicit price of environmental variables*

According to (2), it is easy to show that with a SEM model, the implicit price is equal to estimate of β if the hedonic regression is linear and consequently does not depend on neighboring observations.

On the contrary, the SAR and the SDM models have to be rewritten in their reduced form (assuming the matrix $(I - \rho W)$ is not singular):

for the SAR model

$$P = (I - \rho W)^{-1} X\beta + (I - \rho W)^{-1} \alpha i_n + (I - \rho W)^{-1} \epsilon, \tag{4}$$

for the SDM model

$$P = (I - \rho W)^{-1} X\beta + (I - \rho W)^{-1} \alpha i_n + (I - \rho W)^{-1} W X \theta + (I - \rho W)^{-1} \epsilon, \tag{5}$$

This implies that the implicit prices of the housing attributes depend on W as well as on $\hat{\rho}$ and on $\hat{\theta}$. In general case, the vector of implicit prices of an attribute, IP, can be written as:

$$IP = M_{ENV}, \tag{6}$$

where

$$M_{ENV} = (I - \hat{\rho} W)^{-1} \begin{bmatrix} \hat{\beta}_{ENV} & \hat{\theta}_{ENV} w_{12} & \cdots & \hat{\theta}_{ENV} w_{1n} \\ \hat{\theta}_{ENV} w_{21} & \hat{\beta}_{ENV} & \cdots & \hat{\theta}_{ENV} w_{2n} \\ . & . & . & . \\ \hat{\theta}_{ENV} w_{n1} & \hat{\theta}_{ENV} w_{n2} & \cdots & \hat{\beta}_{ENV} \end{bmatrix} \tag{7}$$

In the case of SLX and SDEM specifications, the vector of implicit prices of environmental variable X_{ENV} can be written as:

$$IP = M_{ENV} = \begin{bmatrix} \hat{\beta}_{ENV} & \hat{\theta}_{ENV} w_{12} & \cdots & \hat{\theta}_{ENV} w_{1n} \\ \hat{\theta}_{ENV} w_{21} & \hat{\beta}_{ENV} & \cdots & \hat{\theta}_{ENV} w_{2n} \\ . & . & . & . \\ \hat{\theta}_{ENV} w_{n1} & \hat{\theta}_{ENV} w_{n2} & \cdots & \hat{\beta}_{ENV} \end{bmatrix} \tag{8}$$

Table 1 summarizes the calculation of the MWTP for different spatial hedonic specifications. They involve calculating implicit price estimations in greater detail: it is defined as a *total effect* by the sum of a *direct effect* and an *indirect effect*. Following LeSage and Pace (2009), the diagonal terms M_{ENVii} of the matrix M_{ENV} capture the direct effect of the environmental attribute and the non-diagonal terms M_{ENVij} capture its indirect effect. More precisely, through the direct effect, a measure of a change in the characteristic of the house i is captured considering that the house i is connected to neighboring houses j which will be affected and then impulse feedback effects on the house i (LeSage, 2008). The indirect effect measures the impact on each house i of changes on the characteristic of their neighboring houses. An aggregate measure for all observations is the average of the corresponding terms as suggested by LeSage and Pace (2009). Finally, the total effect as the sum of the direct and indirect effects captures all the changes arising from all the houses through the propagation pattern defined by the W matrix. Table 1 details the form of the effects and of the propagation process in terms of spillovers (Anselin, 2003) for the spatial specifications.

For a SEM, a SDEM and a SLX model the effects are given by the coefficient estimates (equations 9 and 10) and the propagation process is local. In fact, applying the definitions gives the following expressions:

$$DE = \hat{\beta}_{ENV}, \tag{9}$$

$$IE = \frac{1}{n}\hat{\theta}_{ENV}\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij} \tag{10}$$

In a SEM, $IE = 0$ and in SLX or SDEM, $IE = \hat{\theta}_{ENV}$ when W is row standardized ($\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij} = n$).

For a SAR and a SDM model, the spatial multiplier effect supports a global form of spillovers and the effects don't reduce to estimated coefficients but are calculated as given above.

Taking care of this methodology, our environmental evaluation is driven on the *Basse Loire* area.

3 Study area and data description

3.1 Study area

The empirical model is developed for nine cities in the region known as *Basse Loire.* which cover the estuary of the Loire, an important French river which empties in the Atlantic Ocean near the city of Saint Nazaire (Figure 1). Estuaries develop many environmental amenities and are subject to many anthropization factors. In the Loire estuary the fresh river water meets the saline water of the ocean, which gives rise to wide natural areas: the Natural Regional Park Brière with various wetlands (secondary rivers and channels) in the North, the Atlantic coast on the West, and marshes and wetlands in the South.

In this country, the coastline mixes sandy coves and rocky areas and the waterfront has been preserved by local planning such as the development of coastal paths. The country is also characterized by a high level of classified economic activities concentrated in the industrial zone named *Port de Nantes - Saint-Nazaire*: oil refinery, fertilizer plant, shipyard and aviation plant. Many industries are listed in the European and French registers of pollutant emissions and/or in the SEVESO classification.

In other parts, the *Basse Loire* is more a suburban and a rural area. Most of the towns are small with less than 10 000 inhabitants but tends to exhibits dynamics demographic growth over the last decade.[3] According to recent census data (2007) single-family houses represent more than 80% of all housing except for two cities - Paimboeuf and Saint-Nazaire - where the proportion is about 65% and 44%, respectively.

The *Basse Loire* is connected with its regional capital city Nantes and with bordering regions *Bretagne* and *Vendée* via roads and rail links. The main roads have high volumes of traffic which induces noise and air pollutions. Noise pollution from railways is expected to be lower because the high speed train (TGV) goes mainly through the industrial zone.

3.2 Data

Our data set combines information given by two data sources: housing transactions census and GIS data, both available to local administrative jurisdictions. The variables are presented in Table 2. Data on sale price, P, and lot size, LOT, are available from the DIA census (*Déclarations d'Intention d'Aliéner*) which collects all the housing transactions in the towns. Our sample includes 1989 single-family houses, sold from 01-01-2004 to 12-31-2006, and located in 9 cities. On average, a single-family house price is 158 000 euros for an average lot size of 627 m^2. Figure 1 shows the study area and the sold houses. From the DIA database we also obtained the parcel code of the house to match additional geographical features available in the following geographical databases: cadastral data, noise maps and land use GIS.[4]

Each housing transaction is characterized by local attributes in terms of land use, noise pollution or proximity to environmental attributes - natural resources or more anthropized ones - which potentially induced amenities or nuisances.

With a dummy variable $SNAZ$, we distinguish real estate transactions located in the main city of the area (Saint-Nazaire), which concerns 20.6% of the sample, to control for the impact of urban centrality. The general trend from urban to rural places is more precisely described with the Housing Type variable ($TYPE$). It is a qualitative variable which indicates a fairly homogeneous type of building along the urban-rural gradient and is displayed in four types. Two categories refer to contiguous urbanized areas with public transportations, shops and public facilities and two other categories refer to rural areas poorly equipped. *Town Center* (TC) indicates older and denser buildings in the center of a city where houses often have no garage and only a small garden. Then we find larger houses with a garage and larger undeveloped plot in the *Urban Residential Areas* (URA). Two other categories, outside continuous urbanized areas, are defined for isolated clusters of houses: *Rural Housing Development* (RHD) indicates a housing development recently built in countryside while a *Rural Isolated Hamlet* (RIH) indicates a small cluster of older houses in countryside. 60% of the real estate transactions fall in urban styles (TC and URA) and 40% of houses fall in rural styles (RHD and RIH).[5] The urban-rural gradient is associated to a traditional anthropization process pushed by residential and accessibility purposes.

Noise pollution induced by roads ($NOISE$) is associated to four categories $NOISE1$ ("upper" noisy) to $NOISE4$ ("lower noisy) to take account of the different level of traffic and nuisance.[6] $NOISE0$ defines a zone not affected by noisy roads. The corresponding qualitative variable displays in which noisy zone the house is located. Almost 30% of the real estate transactions are affected by a noisy road and among them, 63% are located near secondary roads ($NOISE3$ and $NOISE4$). To account for the impact of the industrial port area, we create a dummy variable ($PORT$) to reflect whether an observation is located closer than 150 meters to this area. If only a small part of the real transactions are concerned (154 houses that is 7.7% of the sample), the proximity to industrial area exerts a possible depressing effect associated to noise, to pollution and to ugly landscape. These environmental attributes are associated to anthropisation processes pushed by urbanization and economic purposes.

Five other environmental variables are defined to capture the impact of natural or undeveloped areas, including the seaboard (SEA), the Loire ($LOIRE$), secondary rivers and channels (RIV), wetlands (WET), and ponds ($POND$). We have defined a buffer of 500 meters around each type of natural area and if the house is located inside the buffer the environmental variable takes the value 1 or 0 otherwise. 17% of the housing transactions are located on the ocean frontage. Note that in these places, housing benefits from a pleasant environment too with neither noise nor industrial nuisance since they are not concerned by the industrial port area and are mostly located outside noisy road zones. We can finally observe that almost 60% of the houses are located near wet natural areas (the Loire, secondary rivers, wetlands or ponds), which underlines the specific environmental value of the estuary area. These environmental attributes are associated to some anthropization processes pushed by the regulation and the preservation of natural areas.

4 Estimation strategy

In a spatial context, the final estimation of the implicit price depends on the spatial specification used (see sec. 2.2). The point is to search the appropriate spatial specification and we consider as the benchmark model, the log-log a-spatial equation, which is the most often used in hedonic studies, with the following explanatory variables (see Table 2):

$$\begin{aligned}\ln P_i = \alpha_0 + \alpha_1 \ln LOT_i + \alpha_2 SNAZ + \alpha_3 TYPE + \alpha_5 NOISE \\ + \alpha_6 SEA + \alpha_7 LOIRE + \alpha_8 RIV \\ + \alpha_9 WET + \alpha_{10} POND + \alpha_{11} PORT + \epsilon, \end{aligned} \tag{11}$$

The estimated coefficients are interpreted as the elasticity of housing prices with respect to the explanatory variables but according to the appropriate transformation for discrete ones.[7]

Technically, to deal with the spatial dimension requires the description of a spatial interaction pattern: the way each observation is connected to each other ones regardless a definition of a neighborhood (sec. 4.1) and a spatial weight design (sec. 4.2). Additional information on potential household behaviors for environmental amenities may be assigned to the spatial dependence patterns. Finally, a selection process is implemented to discriminate between the various spatial hedonic specifications (sec. 4.3).

4.1 The spatial dimension of neighborhood

Speaking of neighborhood dependencies is developed through spatial interaction patterns in spatial weight matrices which are more linked to the mathematical definition of neighborhood and to the concept of external effect in economics. The spatial weight matrix describes for each observation in the sample which other nearby observations may be considered as its neighbors - i.e. potentially influence it - and with which level of intensity.

Note that the neighborhood variables which are directly included in the hedonic specification (equation 1) play a different role: all observations in the same neighborhood - i.e. a small area - share the same attributes. For example urban planners usually define neighborhoods as areas impacted by the same effect because they are exposed to same risk (flood, noise, industrial risk...) or because they benefit from the same measures of preservation, either patrimonial or environmental.

With spatial dependence, one house can be located in a "neighborhood" whereas its neighbors - connected houses - are located in adjacent but different "neighborhoods".

In other words, the price of one house capitalizes the implicit values of local amenities (open space in a green neighborhood or air pollution of roads...) - i.e. impact of a neighborhood variable - but is also affected by the value of nearby houses either located in the same neighborhood or not - i.e. external effect. We can then suppose that the price of a house located at the edge of a green neighborhood may be different of the price of a house located in the middle of this green area because they don't necessarily have the same set of neighboring houses. Taking care of spatial dependencies allows overlapping effects and prevents from imprecise or wrong appreciation of neighborhood delimitation (Dubin, 1992).

In hedonic environmental applications of spatial econometrics models, the most widely used definition of a neighboring house is based on physical distance between houses (Bell and Bockstael, 2000).

The observations i and j are neighbors if $d_{ij} \leq r$, where d_{ij} is an Euclidian distance between the observations and r is an exogenously chosen radius.

For each house, the size of its neighbors' set is then supposed to increase as the radius enlarges but even more for houses located in dense areas than in dispersed housing districts.[8] If we transpose this heterogeneity between central area and peripheral areas to the household's behavior during his housing search process, it means that more information is collected in central areas than in peripheral ones (see Figure 2).

In our case study, the changes in neighborhoods' sets for increasing values of r (from r = 500 meters to r = 4000 meters) are displayed in Table 3. It shows that with a mean of 46 neighbors (for r = 500 meters), 26 observations have no neighbors, 13 observations have only one neighbor, and 2 observations have more than 122 neighbors (that is three times the average number). If r = 2500 meters, the average size of neighborhood's sets is

388 neighbors but there is still 1 observation without neighbors and 2 observations with only one neighbor whereas 1 observation has more than 810 neighbors. In fact, jumping to 3000 meters allows each observation to have at least one neighbor. For this radius, each observation is on average linked to one fifth of the sample. We can also observe that the average number of neighbors increases by 90 or so when the radius increases by 500 meters. Then the set of information about houses and their attributes gains a lot of new and probably heterogeneous items at every step.

Another design for a neighbor's set in spatial analysis is then to choose a set of k-nearest observations: each house has exactly k neighbors.

The observations i and j are neighbors if $d_{ij} \leq d_{ik}$ where d_{ik} is the maximal distance such that the observation i has exactly k neighbors: d_{ik} is then specific to the observation i (Figure 3).

The distance d_{ik} is probably smaller in dense areas than in dispersed ones: neighbors of isolated observations could be located at high distance from them, while for observations located in high density urban areas, nearest observations will be really close (see Figure 4). As the constant 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 anywhere the household is searching a house, a same amount of information is needed.

Table 4 shows the distribution of distances for increasing values of k. Even if 75% of the houses of the sample have their first nearest neighbor located at 70 meters, some observations are distanced from the nearest one by more than 2 500 meters. Not surprisingly the maximal distance increases to find a constant but larger number of neighbors: from 2 512 meters ($k = 1$) to 7 721 meters ($k = 50$). Looking at the distance distributions shows that a radius of around 515 meters matches the average neighborhood within which a household can find 50 houses to compare with. Moreover, at least 75% of the 50 nearest neighbors required are found within a neighborhood of 543 meters in radius.

To sum up the two neighborhood designs for our case study we assume that a local view of information research is set within a radius of 500 meters: such neighborhoods allow covering at least 75% of the k nearest housing required for the household. Increasing the number of k nearest houses brings here more detailed information within a small neighborhood. To increase the radius of the neighborhood gives additional information brought by other houses (if required for the k nearest neighbors case) and matches a more global process of information research going so far as to cover the whole urban area.

4.2 The spatial weight matrix

The spatial weight matrix helps to model the intensity of interaction between two observations: it gives the weight of the information about two neighboring houses and their attributes.

A spatial weight matrix W is a square $n \times n$ matrix whose terms $w_{ij} \neq 0$ iff the observations i and j are defined as neighbors and where $w_{ii} \equiv 0$ by convention.

In environmental literature, the two most commonly used spatial patterns are the contiguity pattern and the distance based pattern.

- In the contiguity spatial matrix, $w_{ij} = 1$ iff i and j are neighbors.[9]
- In the distance based specification, either the inverse distance ($w_{ij} = \frac{1}{d_{ij}}$) or the inverse squared distance ($w_{ij} = \frac{1}{d_{ij}^2}$) values the interaction between the neighbors i and j.[10]

The distance based specification means a decreasing interaction between the house i and its farther neighbors j whereas the contiguity specification means a constant interaction for all neighboring houses j wherever there are located.

To compare spatial analyses drawn with different spatial matrices, a "row standardization" transformation is applied, i.e. spatial weights are transformed so that for each row, the sum of weights is made to sum to unity: $\sum_{j=1}^{N} w_{ij} = 1$.

For the contiguity matrix, if n_i is the number of neighbors of the house i, then the row transformation gives: $w_{ij} = \frac{1}{n_i}$. For the k nearest contiguity specification, it gives: $w_{ij} = \frac{1}{k}$.

We name W_1 the contiguity matrix, W_2 the inverse distance matrix and W_3 the squared inverse distance matrix. We consider two types of neighborhoods: distance threshold (radius) and k nearest neighbors.

In spatial analysis literature, it is assumed that the choice of W is researcher's one, but some *ad-hoc* critics are often underlined. To match the real story is the best way to address this problem. In our case, the household behavior we attempt to describe may guide us. For example, if the household gives more importance to the information from closer houses than from farther ones, then a distance based specification is better. If the importance of information strongly decreases with distance then the inverse squared distance is better. If the household considers information from all neighboring houses as important then a contiguity specification is better. The size of the neighborhood (the value of the radius r or the number k) is questioned too. For the distance based specifications, the value of r or k has less consequence, because of decreasing interactions, than for the contiguity specification. In the latter case, a maximum value for r or k can be based on a pragmatic size for the prospection area.

Our strategy of matrix selection will be detailed in section 5.

4.3 Spatial equation selection

Three specification search approaches are proposed in spatial econometrics: *Specific-to-General*, *General-to-Specific* and "*Story*". Until recently, the first one was widely used but the second approach is now more and more advised while the third one is the researcher's own point of view. We briefly present the methodology of each method and discuss their relative strengths or weakness given the fact that neither stable guidelines nor consensus have been proposed yet.

The *Specific-to-General* approach consists to test for spatial dependence in a specific model - i.e. without spatial coefficient to estimate like the "OLS" benchmark model[11] (equation 11) or the SLX model (equation **??**) - and to test whether a more general model - i.e. including spatial coefficient like the SAR or SEM models (equation **??** and equation **??**) - is statistically more appropriated. The *Specific-to-General* approach is step by step implemented (see Figure 5(a)-(b)).To discriminate between the two forms of spatial dependence[12] - spatial autocorrelation of errors - SEM - or endogenous spatial lag - SAR - a *decision rule* is advised (Anselin and Florax, 1995; Anselin et al., 1996): it is based on two Lagrange Multiplier Tests (LMERR and LMLAG) and their robust versions (R-LMERR and R-LMLAG).[13] When the choice of the SEM model is suggested, a next step is needed: the Common Factor test should be used to choose between the SEM specification and its extensive form as a SDM model (Mur and Angulo, 2006). Finally, the appropriate estimation of implicit prices is obtained since as seen in Table 1, these estimations are different if we have a *nuisance* (SEM) or *substantive* (SDM or SAR) spatial autocorrelation forms.

A *General-to-Specific* approach, discussed for example by Vega and Elhorst (2013), involves to start with the most general model (SDM or SDEM in our case) and to test if these models are more appropriated then different constrained specifications. A step by step process, displayed in Figure 5(c), is implemented using the tests.[14] Thereby we test SDM model against SAR model ($H_0 : \theta = 0$), SLX model ($H_0 : \rho = 0$) or SEM model ($H_0 : \theta = -\rho\beta$). The SDEM model is tested against SLX model ($H_0 : \lambda = 0$) and SEM model ($H_0 : \theta = 0$). At the next step, each model (SAR, SLX or SEM specification) is tested against "OLS" model. The appropriate specification is then used to calculate the implicit prices of environmental variables (Table 1).

Finally the *"Story"* approach is pushed either by empirical or theoretical aims.[15] In the former case, common knowledge draws towards the most appropriate specification. A SAR specification is often chosen in hedonic housing studies because the market makes the prices. The Spatial Lag of Explanatory Variables specification (SLX) helps to capture spatial externalities arising from housing and neighborhood attributes and to identify some local market features. For example it is clear that to live in a preserved district or near a beautiful landscape seems better than to live in a degraded district or close to a polluting site. Another alternative is to focus on the SEM specification as a correction form for many problems: model miss-specification, omitted variables and measurement errors... In the latter case (theoretical reason), a spatial specification is drawn from a structural model but no spatial hedonic specification has been established yet from a structural housing model.

However, to this point, spatial econometrics is not fundamentally different from other econometrics fields and our remaining goals are to address a robust methodology and to give a reliable estimation of implicit prices for environmental variables.

5 Estimation results and interpretations for environmental evaluation

5.1 Robustness analysis

It is in fact unavoidable that implicit price values will vary with different spatial weight matrices either in terms of neighborhood designs (contiguity W_1, inverse distance W_2 and inverse squared distance W_3) or in terms of neighborhood size (length of the radius r and number k of neighbors). Here, the robustness analysis helps to identify whether the choice of particular W matrices induces some discordant results and provides empirical guidelines to be discussed with realistic features. Moreover, the selection of the appropriate specification may be sensitive to the spatial weight configurations. In that case, the robustness analysis helps to identify the specification that most frequently occurs and that will be used to calculate the proper implicit prices for housing and environmental attributes.

For each three types of neighborhood design (W_1, W_2 et W_3) we consider an increasing size for the set of connected houses: the radius r increases by a 500 meters step from 500 meters to 4 000 meters (8 cases) and the number k of nearest neighboring houses increases by a step of 5 new houses from 5 to 50 (10 cases). Fifty four cases are then considered.

As a first result, we test whether the distribution of housing prices per m^2 is spatially autocorrelated and performs the traditional Moran's I statistic. We show that prices per square meters are spatially and positively autocorrelated whatever the W matrix used (Table 5 reports the average values of Moran's I for small and large sets of neighbors).

Housing price in one place is then dependent on housing prices in neighboring places: household may expect higher prices in well valued places and smaller prices in disadvantaged areas. Starting the comparison process in small neighborhood, with closer houses, gives Moran's I values ranging from 0.208 to 0.421 on average. When the comparison process spreads over further houses, spatial dependence is still present and tends to decrease (Moran's I values ranging from 0.113 to 0.405 on average) but with smaller magnitudes with the k nearest neighbors design or the inverse squared distance interactions (W_3 matrix) than with radius neighborhood design or contiguity interactions (W_1 matrix).

These results in accordance with many spatial analyses of housing prices reveal the local features of the housing price distribution and three cases detailed above (see sec. 4) are evidenced. As expected, for the smallest radius neighborhood ($r = 500$ meters) and the larger k nearest neighbors designs, the Moran's I values are quite similar since a household will find 46 neighboring houses on average within a radius of 500 meters. On the contrary, for very large circles, very large sets of neighboring houses are considered with more heterogeneous information and spatial autocorrelation weakens as expected. Finally, for both radius or nearest neighbors designs, the interaction patterns based on distance (W_2 and W_3) tend to soften the influence of heterogeneous information brought by the furthest houses: household's opinion will then be less influenced by their prices and attributes than with the contiguity interaction pattern (W_1).

5.2 Estimation results

The selection specification is based on the *General-to-Specific* approach and on the *Specific-to-General* approach and all estimations and tests are performed using the *spdep* package of the R software (Bivand et al., 2008). Results are synthesized in Table 6.[16]

The *Specific-to-General* approach for the "OLS" equation (Figure 5(a)) leads to mainly select the SDM specification for small neighborhoods and the SAR specification in some cases for large neighborhoods. The *Specific-to-General* approach for the SLX equation (Figure 5(b)) leads to mainly select the SDM or SDEM specifications. We never reject the absence of spatial dependence and discriminate in favor of "substantive" spatial dependence which works by means of endogenous spatially lagged variables only (SAR model), both endogenous and exogenous spatially-lagged variables (SDM specification) or in favor of "nuisance" spatial dependence (SDEM specification) in some cases (see Table 1).

The *General-to-Specific* approach conclusions are in favor of different selected specifications (SLX, SDM or SDEM) according to the W matrices. The spatial dimension of housing prices is underlined either with exogenous spatially lagged variables or spatial dependence parameters.

These results may be interpreted as follows: households are aware of getting more or less detailed information about the attributes of neighboring houses. They pay attention to the price of neighboring houses but they don't neglect the exact contribution of the attributes even when they increase the comparison area.

In all cases, neither the "OLS" equation nor the SEM specification have been selected. This implies that the estimated implicit prices of environmental attributes don't reduce to the estimated coefficient associated to the corresponding environmental variables ($\hat{\beta}_{ENV}$). As it is shown in Table 1, the implicit prices are given by the total effect and adds two results (a direct effect and an indirect effect) to combine, according to the estimated model, $\hat{\beta}_{ENV}$ and $\hat{\theta}_{ENV}$ with a spatial transformation involving $\hat{\rho}$. Ignoring the spatial dimension in housing price formation leads to inadequate environmental evaluation. remonter dans Robustness analysis

All estimations, using the appropriate spatial equations and W matrices are synthetized by three results: (i) either the attribute is significant or not, (ii) if significant, the magnitude of its impact on housing price - i.e. the estimated MWTP - and (iii) the way the spatial organization of housing markets affect the households' perception of implicit prices. Let us recall that we initially consider 54 spatial weight matrices and the selected spatial equations (SLX, SDEM and SDM). However, given the robustness analysis drawbacks, we only present the estimated implicit prices corresponding to the five cases as in Table 5: for $r = 500$ meters, for small k values, for large k values, for small r values and for large r values.[17] Results for each significant variable are presented in Figures. Table 7 displays some examples which help to compare our results with others obtained by inappropriate methods: (i) OLS which provides potentially inefficient or biased estimations since it doesn't take into account spatial dependence and (ii) for a selected of spatial specifications (SDM and SLX for instance) when the implicit prices are given by the estimated coefficients of explanatory variables instead of the total effects. Given the general comments previously underlined and confirmed by the upcoming comments, we choose to consider a neighborhood design based on W_3 and $k = 50$ for the two spatial hedonic examples: for this design, 75% of the households collect information on housing prices and on housing attributes in a small area (within a neighborhood by around 500 meters) and gives more importance to the closest houses.

Before focusing on the impacts of the environmental variables we first comment the other determinants of housing prices.

Concerning the housing attributes, we estimate a positive and significant implicit price of the lot size: housing price more precisely increases at a decreasing rate with its lot size (LOT) since the elasticity is lower than 1 (cf. Figure 6). Estimated total effects are similar enough whatever the neighborhood design (r or k) and the interaction patterns (W_1, W_2 or W_3) but with more stable values when the information brought by the furthest houses is softened as for the W_2 or W_3 interaction patterns. The household is willing to pay around 2.4% higher for a 10% larger sized lot (Table 7, columns 8 and 11). Do not consider neither spatial effects (OLS, column 2) nor correct estimated values ($\hat{\beta}$ coefficient instead of the total effect in the SDM model in the example, columns 4 and 8) induces an overestimation of around 3% in the first case (0.247 instead of 0.239) and of around 7% in the second case (0.254 instead of 0.239).

The residential zoning mainly affects the housing prices through the urban-rural gradient. Households are willing to pay lower prices to live in rural housing developments instead of living in the center of the towns with total effects ranging on average from -0.1 to -0.175 with the W_2 and W_3 designs (cf. Figure 7). The magnitude of this effect, in terms of elasticity, results in a decreasing value of the house built in rural development programs between 10% and 15% compare to the value of a house built in the center of the towns. To live in a rural isolated hamlet is even more depreciating with total effects amount to -0.25 on average (cf. Figure 8) which correspond to a depreciation, measured in elasticity, of the property value of about 22% compare to the center of the town. In the SLX example (Table 7, columns 9 to 11) do not consider the spatial effects leads to overestimate these depreciations: the elasticity of living in a rural housing development is about -11.1% (total effect, column 11) against -13.5% (OLS, column 2) and for rural isolated hamlet the elasticity is about -20.3% (total effect, column 11) against -26.3% (OLS, column 2). Moreover, calculating the MWTP with the estimated values of the beta coefficient only induces an overestimation of nearly the twice of the correct values (columns 9 and 11): -0.245 against -0.118 for rural housing development and -0.402 against -0.227 for rural isolated hamlet. It leads to incorrect bigger estimations of the elasticities of living in a rural housing development (-21.7% against -11.1%) or in rural isolated hamlets (-33.1% against -20.3%). In urban areas, living in peripheral residential areas (URA) rather in downtown makes no difference to the households. They are no more willing to pay to locate in the major city of the estuary (Saint Nazaire) since the coefficient of the dummy variable $SNAZ$ appears as not significant in almost all spatial hedonic equations estimated. The significant and positive effect estimated by the OLS model, even small, is then invalidated by the presence of spatial dependence.

Spatial effects are not neutral and total effects have to be estimated. Spatial dependence patterns allowing to capture local information and to control for heterogeneous spatial distribution of attributes provide stable estimations of such total effects. W_2 and W_3 neighborhood designs are then preferred. Applied to environmental variables, such interpretation learnings help to evaluate the effects of natural resources and more anthropized environment in the estuary of the Loire.

5.3 Environmental evaluation results

Regarding to natural resources, households are aware of proximity to the sea (SEA), proximity to secondary rivers or channels (RIV) and proximity to wetlands (WET) whose total effects are significant in almost all estimated cases (cf. Figures 9 to 11). On the contrary, to be located near the main river ($LOIRE$) or ponds ($POND$) has no impact on housing prices since estimated coefficients are never or rarely significant. We expect nuisance from the environmental variables produced by high anthropization but only the effect of upper middle noisy roads ($NOISE2$) is significant in almost all cases (cf. Figure

12). The impacts of other noisy roads ($NOISE1$; $NOISE3$; $NOISE4$) and the proximity to the industrial-portuary area ($PORT$) are rarely or never significant.

We recall what is precisely the role played by the spatial dimension to render our interpretations clearer. The impacts on housing prices are spatially defined: the housing price in one place depends on the price of houses located in other places. In this way, induced effects - spatial externalities - across neighboring houses and related to their attributes are capitalized into implicit prices and must not be ignored. To give the correct interpretation of estimations, we have calculated the total effect of each significant environmental variable. Moreover, spatial hedonic specification improves the environmental evaluation by considering that the implicit value depends both on an "absolute" attribute (being or not being located close to the ocean frontage for example) captured for example by a dummy variable and on a "relative" attribute which depends on the spatial distribution of this characteristic among the other houses: the fact that more or less houses are located close to the ocean frontage or at very farther places affects the implicit value. According to the spatial interdependence patterns, a spatial externality propagates across the estuary whose impacts are taking into account in the households' MWTP for environmental amenities. The decomposition of the total effect between a direct effect and an indirect effect illustrates the propagation mechanism as described in the section 2.2 of the paper. It is worth recalling that even with small neighborhood sets, the propagation mechanism covers all the space as due to the spatial inverse transformation (see Table 1). Using this methodology, we give detailed results for the proximity to the sea as an expected amenity and the proximity to the upper middle noisy roads as an expected nuisance and we start briefly commenting the case of the two other estuary amenities: proximity to wetlands and to rivers.

The total effects for these amenities are negative and stable whatever the spatial hedonic specifications and spatial dependence patterns (see Figure 9 for proximity to secondary rivers and channels and Figure 10 for proximity to wetlands). Estimated total effects for wetlands range from -0.2 to -0.25 on average and are stronger for streams since they amount to -0.4 on average. With our SDM and SLX spatial hedonic examples (Table

7, colomns 8 and 11), to be located close to wetlands decreases the price by 23% and proximity to rivers or channel decreases housing prices by 34%. The negative impact of proximity to wetlands and streams has been yet observed in hedonic literature, in the metropolitan area of Portland, Oregon (USA) (Mahan et al., 2000), while Doss and Taff (1996) find that negative effects are observed when real estate properties located not too close of wetlands in the Minnesota (USA). In our case, the negative impact is supported by the surrounding properties since direct effects are positive but not significant. Flood risk is of course negatively assessed by households but these results suggest that housing densities near such natural areas are negatively desired by households: more houses near wetlands or streams induce a global depreciation of housing values near these areas. While this negative effect is detected by OLS estimation, even if it is not reliable due to spatial dependence effect (Table 7, column 2), the implicit price estimate must not be given by the beta coefficient (table 7 columns 4 for SDM or column 9 for SLX) which is rather false and not significant.

Concerning the proximity to the ocean frontage, as expected, households value the proximity to the sea with a marginal willingness to pay ranging on average from 0.45 to 0.5 (Figure 11(a)) when they attach more importance to closer houses (W_3 design) but increasing more and up to 0.8 when households attach importance to further houses too (W_2 and larger r or k). The magnitude of the positive total effect of the seaboard proximity to housing price is consistent to previous studies. With the SDM and SLX examples (Table 7, colomns 8 and 11) the estimated elasticities are about 57% whereas Bin et al. (2011) found an increase of the property values in North Carolina between 56.3% and 77% for ocean frontage. Milon et al. (1984) estimated that housing price declined 36% in moving 500 feet (120 meters) from the Gulf of Mexico. We underline that ignoring spatial effects leads to a wrong estimation of the elasticity: it is 11% lower with OLS estimation (Table 7, column 2). We can therefore observe that when the neighborhoods extend, covering larger areas with potentially more houses outside the ocean frontage, the implicit prices increase (cf. Figure 11(a)) because the comparison process involves the both types of houses and the differences between a location close to the ocean or far from the ocean may be integrated by the households. The decomposition of the total effect between the direct effect and the indirect effect illustrates this point (cf. Figure 11(b)). Whereas direct effects are negative (and not significant in most cases), indirect effects are strongly positive: the marginal willingness to pay for the proximity to the sea is driven by the neighboring houses. The difference between a neighborhood far from the ocean frontage and a neighborhood close to the ocean is enhanced by 0.61 or 0.69 (Table 7, columns 7 and 10) even if the household seems not appreciate to pay for living near the sea (direct effect is negative, Table 7, columns 4 and 9).

A growing purpose of environmental evaluation concerns the effects of nuisance. In urbanized areas, transportation infrastructures are essential to access to jobs and to all services but with indissociable noise troubles and air pollution effects due to traffic. In the estuary, three roads are classified as upper middle noisy. They connect smaller roads to the highways and to major roads towards regional cities (Map on Figure 1). Implicit prices are positive but with decreasing values as far as neighborhood extend (Figure 12(a)). The magnitude of the implicit prices rises from 10% to 22% for spatial dependence patterns valuing local surroundings (k nearest neighbors and W_2 or W_3 spatial interactions). In fact, spatial hedonic models capture a significant and positive effect whereas the OLS estimation fails to value it (Table 7, column 2). For the SLX model (Table 7, columns 9 to 11), the proximity to these roads increases the price of houses by 11.3%. If we don't implement the spatial transformation to the beta coefficient (column 9) we come to the wrong conclusion in favor of a strong nuisance which decreases the housing price by 31%. On the contrary, the positive total effect reveals that households balance between nuisance and accessibility as showed by the decomposition between the direct and indirect effects (Figure 12(b)). The negative direct effect of a place affected by a road of level 2 reveals the nuisance effect and local congestion within the classified zone $NOISE2$. The positive indirect effect values the general accessibility over the area which is facilitated by the main roads connected to local roads and to highway that connects the study area with the regional capital as well as with neighboring regions. The positive impact of the mobility and negative impact of the traffic noise have been already observed in the hedonic literature.

For example, in the urban area of Glasgow (Scoltland) Bateman et al. (2001) found a negative effect for the traffic noise and for the view on the roads but a positive effect of the travel time to railway station.

Finally, in the estuary of the Loire, housing values are subject to many strengths driven by the housing attributes, the environmental attributes and spatial spillovers. When focusing on environmental features, expected positive impacts are concentrated on traditional attributes like the proximity to the ocean frontage and quiet places. On the contrary, the presence of various natural wet amenities is negatively valued because of the impression of housing density associated to flood risk. If urban places are more valued by households, it's rather because rural location are less desired than because of urban intrinsic attributes.

Conclusion

Our paper contributes to environmental evaluation in three directions. First we associate anthropization to environmental attributes. Hedonic models applied to housing values are chosen to estimate the implicit prices households are willing to pay for environmental attributes. Since human behaviors and human actions are responsible for the anthropization of natural resources, it seems interesting to use such models: households evaluating changes driven by human actions. Second we define an empirical strategy to capture spatial interdependencies and improve estimations of implicit prices. In fact, among many challenges raised by environmental evaluation, the spatial distribution of characteristics combined with spatial externalities must not be ignored. Spatial hedonic models have been often used but in our paper we consider that the spatial dimension of data is rarely entirely or accurately capture since feedback and propagation effects are not questioned. In our paper, we manage to value them through the estimation of direct effects and indirect effects. Third, we implement an empirical strategy based on 54 types of spatial interdependence designs to test the robustness of our estimates. We show that spatial dependence patterns based on inverse distance and small neighborhoods provide stable estimations. It is consistent too with household behaviors: information on closer housings is more reliable and comparison areas are in fact limited by the research process.

Implicit prices for housing attributes and environmental variables are empirically estimated in the estuary of the Loire, a French area well occupied by natural spaces and artificialized ones. As expected, the proximity to the ocean frontage increases housing values but we show that these larger prices are enhanced above all by larger prices of neighboring houses and don't depend on pure seaboard amenities. In other words, implicit prices for seaboard proximity are supported by the market. Proximity to roads is positively valued too revealing that accessibility prevails over noise disturbance. Finally, the presence of various natural wet amenities depreciates housing values revealing that residential choices probably suffer from flood risks.

Our methodology is a first step to estimate spatial propagation of environmental values. It may be develop in two directions: a better understanding of human behaviors behind this propagation process for better environmental policies. If households value environmental attributes of housing, we can expect that the presence of an eco-district, for instance, would increase housing prices and would push towards the developments of eco-districts in neighboring places.

Notes

[1]In the remainder of the paper, we use environmental characteristics, environmental attributes or environmental variables as synonyms if it doesn't carry misinterpretation.

[2]Decker et al. (2005) for example use a log-log specification with respect to environmental variables and stress that the estimated coefficients of environmental attributes can be viewed as elasticities of price to these attributes. The authors report the estimations and the MWTP which are different from coefficients.

[3]The average population growth rate in the study area is about 9%-10% for the period 1999 - 2007 against 5% for the metropolitan French population during the same period. (Sources: census reports RP1999 and RP2007 of the French National Statistical Institute: INSEE).

[4]*MapInfo GIS software* has been used to build the housing types and the environmental neighborhood variables. The digitized cadaster data base is available from the local authorities named *CARENE* and *Sud Estuaire*. The land use GIS *BD MOS44* is available from the *General Council of the Loire-Atlantique* (departmental jurisdiction). The noise maps, available from the the *Departmental Direction of Equipement of the Loire-Atlantique* (regional subdivision of the Department of public works) has been produced by its *CETE Service* in 2008.

[5]These types are defined with the land use GIS *BD MOS44*.

[6]Four sectors affected by noisy roads are defined by the Articles R 571- 32 to R 571-43 of the French Environmental Code. The roads concerned are those with average traffic exceeding 16,400 vehicles per day. Category 1 defines the noisiest road whereas category 4 is for the least noisy one. A Zoning Map is defined for each French local jurisdiction.

[7] For dummy variables, the one percent impact due to the change from 0 to 1 is calculated as following (Halvorsen and Palmquist, 1980): $100 \times (e^{\hat{d}} - 1)$, where $\hat{d}$ is the estimated value of the coefficient.

[8]In regional economics the principal issue concerns the "*modifiable areal unit problem*", when, the spatial units is a small area resulting from exogenous or arbitrary aggregation processes of points, namely "*the level of aggregation and combinations of contiguous units*" (Anselin, 1988, p.26). In our case as in many hedonic environmental valuation studies it is not so sensitive since a spatial unit is a dwelling, i.e., a spatial point itself and not an area.

[9] See among others, Kim et al. (2003), Anselin and Le Gallo (2006), Dekkers and van der Straaten (2009), for examples in environmental hedonic studies.

[10]Many of the environmental hedonic studies use distance based specification as Boxall et al. (2005); Hunt et al. (2005); Cohen and Coughlin (2008); Samarasinghe and Sharp (2010); Ma and Swinton (2011).

[11]The 'OLS" model means a model specification including neither a endogenous spatial lag nor a spatial error term.

[12]The Moran's I test adapted to regression residuals (Cliff and Ord, 1981) only indicates the presence of spatial autocorrelation but doesn't advise for the type of spatial dependence.

[13] If LMLAG is more significant than LMERR and R-LMLAG is significant but R-LMERR is not, then the appropriate model is the spatial autoregressive model. Conversely, if LMERR is more significant than LMLAG and R-LMERR is significant but R-LMLAG is not, then the appropriate specification is the spatial error model. If both R-LM tests are significant the smallest one is taken as model specification. The performance of such an approach is experimentally investigated in Florax and Folmer (1992) and in Florax et al. (2003).

[14]Mueller and Loomis (2010) use an alternative Bayesian estimation method to estimate and compare posterior probabilities for SEM, SAR, and SDM specifications of their spatial hedonic model. The specification which gives a highest posterior probability is chosen.

[15]This expression is freely adapted from various researchers's experience and matches with some motivations listed in LeSage and Pace (2009), chapter 2.

[16]Complete results are available upon request from the authors.

[17] To save space, results with SAR specification, are not presented since they don't radically differ from others. All results - estimations of the coefficients, direct effects, indirect effects and total effects for all explanatory variables, all W matrices and all spatial equations - can be obtained from the authors upon request.

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

Model	Interaction	Dependence	Effects	Implicit price	Direct effect	Indirect effect
OLS	-	-	-	DE	$\hat{\beta}$	-
SEM	nuisance	global	unmodeled	DE	$\hat{\beta}_{ENV}$	-
SLX	exogenous	local	modeled	DE+IE	$\hat{\beta}_{ENV}$	$\hat{\theta}_{ENV}$
SDEM	exogenous and nuisance	local	both	DE+IE	$\hat{\beta}_{ENV}$	$\hat{\theta}_{ENV}$
SAR	endogenous	global	both	DE+IE	Mean of diag.elements of $(I-\hat{\rho}W)^{-1}\hat{\beta}_{ENV}$	Mean of off-diag.elements of $(I-\hat{\rho}W)^{-1}\hat{\beta}_{ENV}$
SDM	endogenous and exogenous	global	both	DE+IE	Mean of diag.elements of $(I-\hat{\rho}W)^{-1}[\hat{\beta}_{ENV}+W\hat{\theta}_{ENV}]$	Mean of off-diag.elements of $(I-\rho W)^{-1}[\hat{\beta}_{ENV}+W\hat{\theta}_{ENV}]$

Adapted from Anselin (2003); Vega and Elhorst (2013).

Local/global spillovers in the spirit of the Anselin (2003) classification. He distinguishes between a global and a local range of dependence, and analyzes how this distinction affects the specification of different spatial models. The taxonomy in Anselin (2003) has two dimensions. The primary dimension is whether the spatial correlation in the reduced form pertains only to unmodeled effects (error terms), to modeled effects (included explanatory variables), or to both. The second dimension in the taxonomy is the distinction between global and local spillovers. In the reduced form this comes down to the inclusion of a spatial multiplier $(I-\rho W)^{-1}$ or $(I-\lambda W)^{-1}$ versus a simple spatial lag term using spatial weights W.

Table 2: Variable definitions and summary statistics

Variable	Description (Unit)		
ENDOGENOUS VARIABLE		Median	Mean
P	Net price (euros)	143 000	158 136
HOUSING ATTRIBUTES		Median or Number	Mean or %
LOT	Floor space (m^2)	398	627
SNAZ	Location in downtown Saint-Nazaire (Dummy)	411	20.6
TYPE	Housing located in a: (Discret variable)		
TC	Town Center (reference modality)	307	15.4
URA	Urban Residential Area	891	44.8
RHD	Rural Housing Developpement	732	36.8
RIH	Rural Isolated Hamlet	59	3.0
Environmental variables (natural resources)		Number	%
	Housing located less than 500 meters from the		
SEA	Seaboard (Dummy)	330	16.6
LOIRE	Main river (Dummy)	100	5.0
RIV	Seconary rivers or channels (Dummy)	248	12.5
WET	Wetlands (Dummy)	502	25.2
POND	Ponds (Dummy)	319	16.0
Environmental variables (anthropized)		Number	%
PORT	Housing located less than 150 meters from the Port Industrial District (Dummy)	154	7.7
NOISE	Housing located in a Noize Zone based on road category (Discret variable)		
NOISE1	Upper noisy roads	123	6.2
NOISE2	Upper middle noisy roads	89	4.5
NOISE3	Lower middle noisy roads	227	11.4
NOISE4	Lower noisy roads	135	6.8
NOISE0	Outside any noisy zones (reference modality)	1 415	71.1

Sample size 1989 observations. Data Sources: DIA and GIS "Hedonic Study of the Basse-Loire region".

Table 3: Spatial neighborhoods with respect to neighborhood radius

Radius, meters	Nb of links	% of links $\neq 0$	Average nb of neighb.	Nb of obs. without neighb.	Min of links	Max of links
500	92 570	2.34	46	21	1 (13 obs.)	122 (2 obs.)
1 000	244 846	6.20	123	5	1 (6 obs.)	304 (1 obs.)
1 500	406 946	10.29	204	4	1 (4 obs.)	490 (1 obs.)
2 000	585 266	14.79	294	2	1 (3 obs.)	666 (1 obs.)
2 500	771 352	19.50	388	1	1 (2 obs.)	810 (1 obs.)
3 000	963 670	24.36	484	-	1 (2 obs.)	903 (1 obs.)
3 500	1 141 640	28.86	574	-	2 (2 obs.)	1 031 (3 obs.)
4 000	1 298 568	32.82	653	-	2 (2 obs.)	1 143 (1 obs.)

Sample size: 1989 observations.

Table 4: Distance distribution in neighborhoods (k nearest neighbors)

k nearest neighbors	1^{st} Qu	Median	Mean	3^{rd} Qu	Max
1	18.02	38.73	62.11	70.80	2 512.00
5	50.31	86.35	133.20	141.20	4 826.00
10	77.23	126.80	199.70	208.20	5 472.00
15	98.82	162.00	251.30	262.60	6 080.00
20	117.70	192.30	295.50	308.50	6 153.00
25	135.10	221.30	336.20	352.00	6 308.00
30	152.40	247.90	372.90	393.30	6 377.00
35	169.20	273.10	407.00	434.20	6 432.00
40	183.80	297.30	440.90	473.40	6 511.00
45	199.00	320.10	476.40	509.30	6 554.00
50	213.70	343.40	515.00	543.90	7 721.00

Sample size: 1989 observations. The minimum of distance between nearest neighbors is 0.

Table 5: Housing prices and Moran's I statistics

	W_1	W_2	W_3
Radius r (meters)			
500	0.267	0.352	0.404
Small [500 - 2000]	0.208	0.315	0.396
	(0.048)	(0.030)	(0.007)
Large [2500 - 4000]	0.113	0.259	0.384
	(0.019)	(0.010)	(0.002)
Nearest neighbors k			
Small [5 - 25]	0.330	0.388	0.421
	(0.031)	(0.022)	(0.010)
Large [30 - 50]	0.270	0.351	0.405
	(0.005)	(0.003)	(0.001)

All statistics are significant at 0.0001 level. Standard deviations are in parentheses.

Table 6: Specification search processes and spatial weight designs

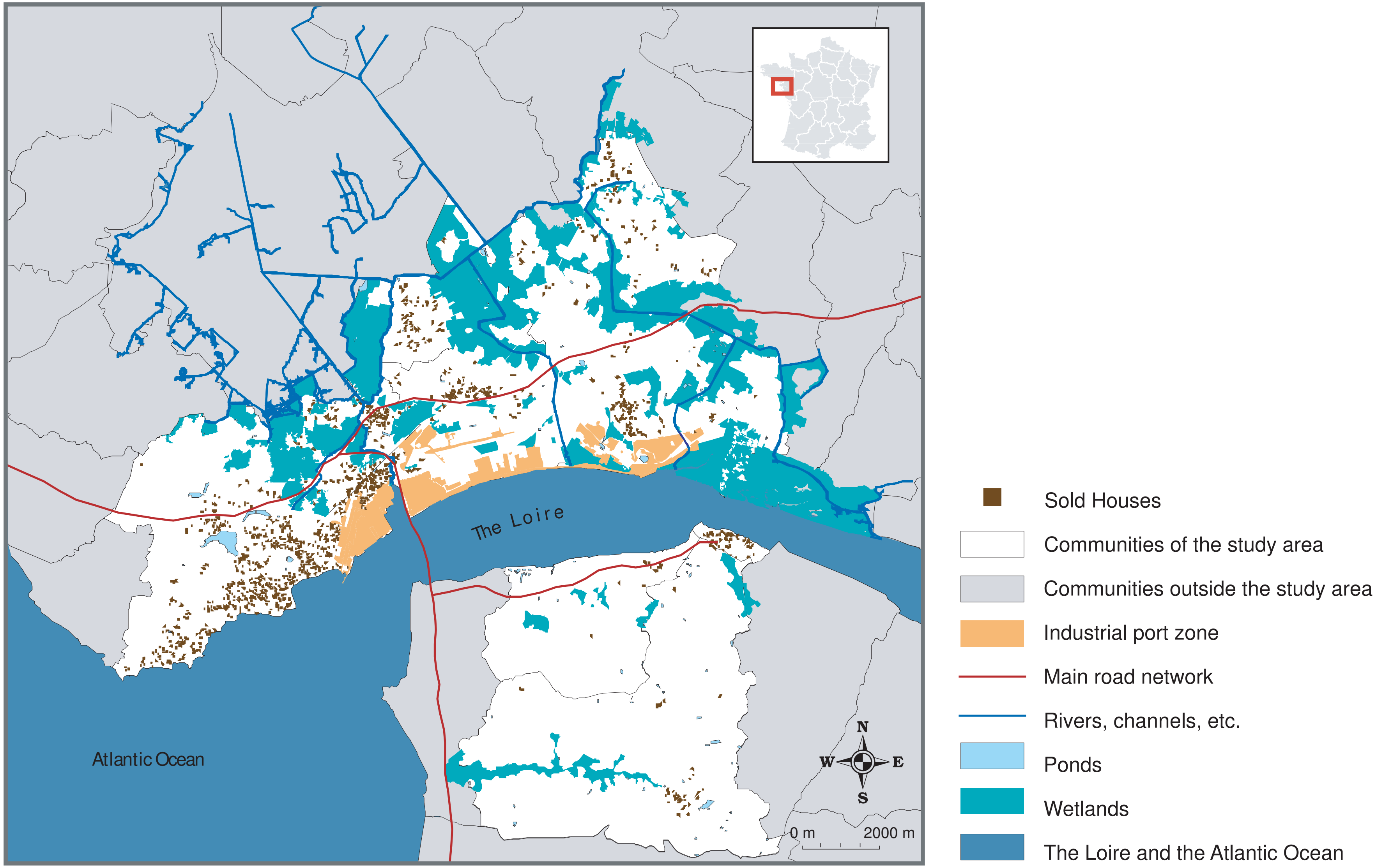
Spatial dependence	W_1 *Contiguity*		W_2 *Inverse distance*		W_3 *Squared inverse distance*	
Spatial neighborhood	r	k	r	k	r	k
Specific-to-General "OLS"	SDM for small sets of neighbors and SAR for larger ones					
Specific-to-General "SLX"	SDM or SDEM					
General-to-Specific	SLX	SDM or SDEM				

Table 7: Implicit price estimates from hedonic specification

Variable	OLS	Spatial	Spatial Hedonic with nearest neighbors (k=50) and spatial inverse squared distance interactions (W_3)							
			Spatial Durbin Model					SLX Model		
(1)	(2) $\hat{\beta}$ (Elasticity)	(3) signif	(4) $\hat{\beta}$	(5) $\hat{\theta}$	(6) Direct Effect	(7) Indirect Effect	(8) Total Effect (6)+(7) (Elasticity)	(9) Direct Effect $\hat{\beta}$	(10) Indirect Effect $\hat{\theta}$	(11) Total Effect (9)+(10) (Elasticity)
Housing attributes										
LOT	0.247^{***}	yes	0.254^{***}	-0.069^{**}	0.253^{***}	-0.014	0.239^{***}	0.252^{***}	-0.012	0.240^{***}
SNAZ	0.083^{**}	no	0.066	-0.011	0.066	0.005	0.071	0.044	0.023	0.067
TYPE_URA	-0.023	no	-0.023	0.030	-0.022	0.031	0.009	-0.022	0.024	0.002
TYPE_RHD	-0.145^{***}	yes	-0.231 .	0.149	-0.225^{*}	0.119	-0.106^{*}	-0.245^{*}	0.127	-0.118^{*}
	$(e = -13.5\%)$						$(e = -10.1\%)$			$(e = -11.1\%)$
TYPE_RIH	-0.305^{***}	yes	-0.382^{**}	0.210	-0.373^{**}	0.152	-0.222	-0.402^{**}	0.175	-0.227^{**}
	$(e = -26.3\%)$						$(e = -19.9\%)$			$(e = -20.3\%)$
Environmental variables (natural resources)										
SEA	0.379^{***}	yes	-0.197 .	0.547^{***}	-0.163	0.614^{***}	0.451^{***}	-0.240^{*}	0.688^{***}	0.448^{***}
	$(e = 46.1\%)$						$(e = 57.0\%)$			$(e = 56,5\%)$
LOIRE	-0.101 .	no	-0.204	0.150	-0.197	0.127	-0.070	-0.224	0.146	-0.078
RIV	-0.386^{***}	yes	-0.001	-0.323^{**}	-0.022	-0.394^{**}	-0.417^{***}	0.005	-0.420^{***}	-0.415^{***}
	$(e = -32.0\%)$						$(e = -34.1\%)$			$(e = -34\%)$
WET	-0.236^{***}	yes	0.039	-0.241^{**}	0.023	-0.284^{**}	-0.261^{***}	0.052	-0.308^{***}	-0.256^{***}
	$(e = -21.0\%)$						$(e = -23.0\%)$			$(e = -22.6\%)$
POND	0.044	no	0.124 .	-0.120	0.118 .	-0.112	0.006	0.126 .	-0.112	0.014
Environmental variables (anthropized)										
PORT	-0.092 .	no	-0.209 .	0.148	-0.202 .	0.123	-0.078	-0.211 .	0.136	-0.075
NOISE1	-0.031	no	0.045	-0.069	0.041	-0.072	-0.031	0.084	-0.116	-0.032
NOISE2	0.025	yes	-0.364^{**}	0.448^{**}	-0.339^{**}	0.447**	0.108 .	-0.373^{**}	0.480^{**}	0.107^{**}
	$(e = 2.5\%)$						$(e = 11.4\%)$			$(e = 11.3\%)$
NOISE3	$-0,059$.	no	-0.079	0.025	-0.078	0.009	-0.069	-0.074	-0.001	-0.075
NOISE4	$0,054$	no	0.029	0.026	0.031	0.040	0.070	0.029	0.048	0.077
Adj. R^2	0.28									
ρ			0.225^{***}							
Res. St Error	0.47		0.45					0.47		

Notes: Number of observations 1 989. Elasticities are given for significant discrete variables
Statistically significance codes: *** - at 0.1%, ** - at 1%, * - at 5%, . - at 10%.
In SDM model inference for direct, indirect and total effects is based on simulation of the impact distributions (equation (6)).

Figure 1: *Basse-Loire* study area



Design: *Masha Pautrel*; Construction: *Claire Choblet, Masha Pautrel*

Sources : *GIS HBLS*; *DGI, Cadaster data base*, available from the CARENE and the CC Sud Estuaire; *BD MOS44*, available from the Conseil Général de la Loire-Atlantique.

Figure 2: *Neighbors' set in a dense area (a) and in a dispersed area (b).*

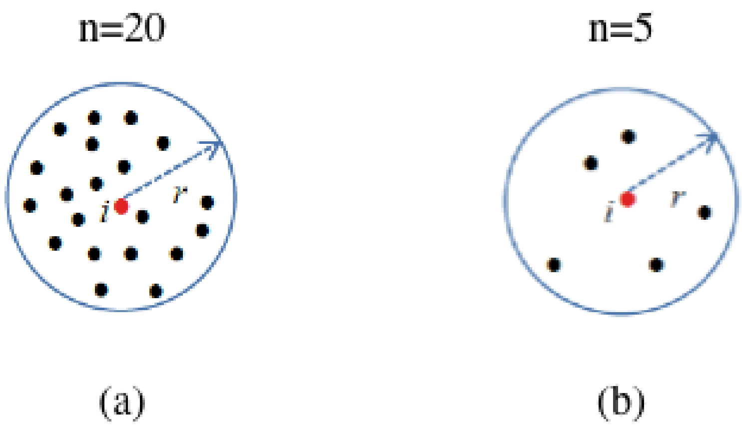


Figure 3: The sets of 9 nearest negihbors for the observations i and j

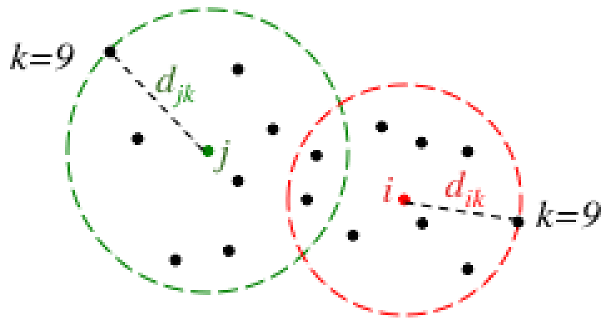


Figure 4: d_{ik} *for* $k = 7$ *in a dense area (a) and in a dispersed area (b).*

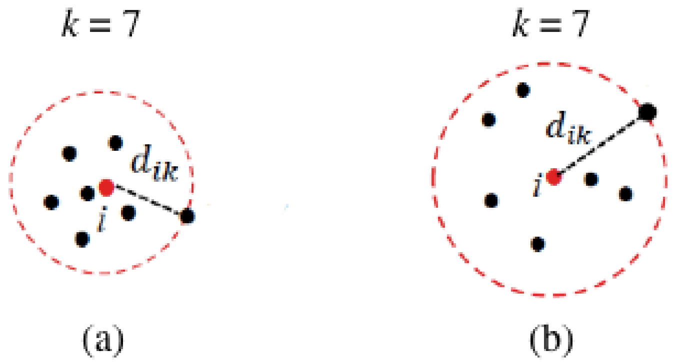
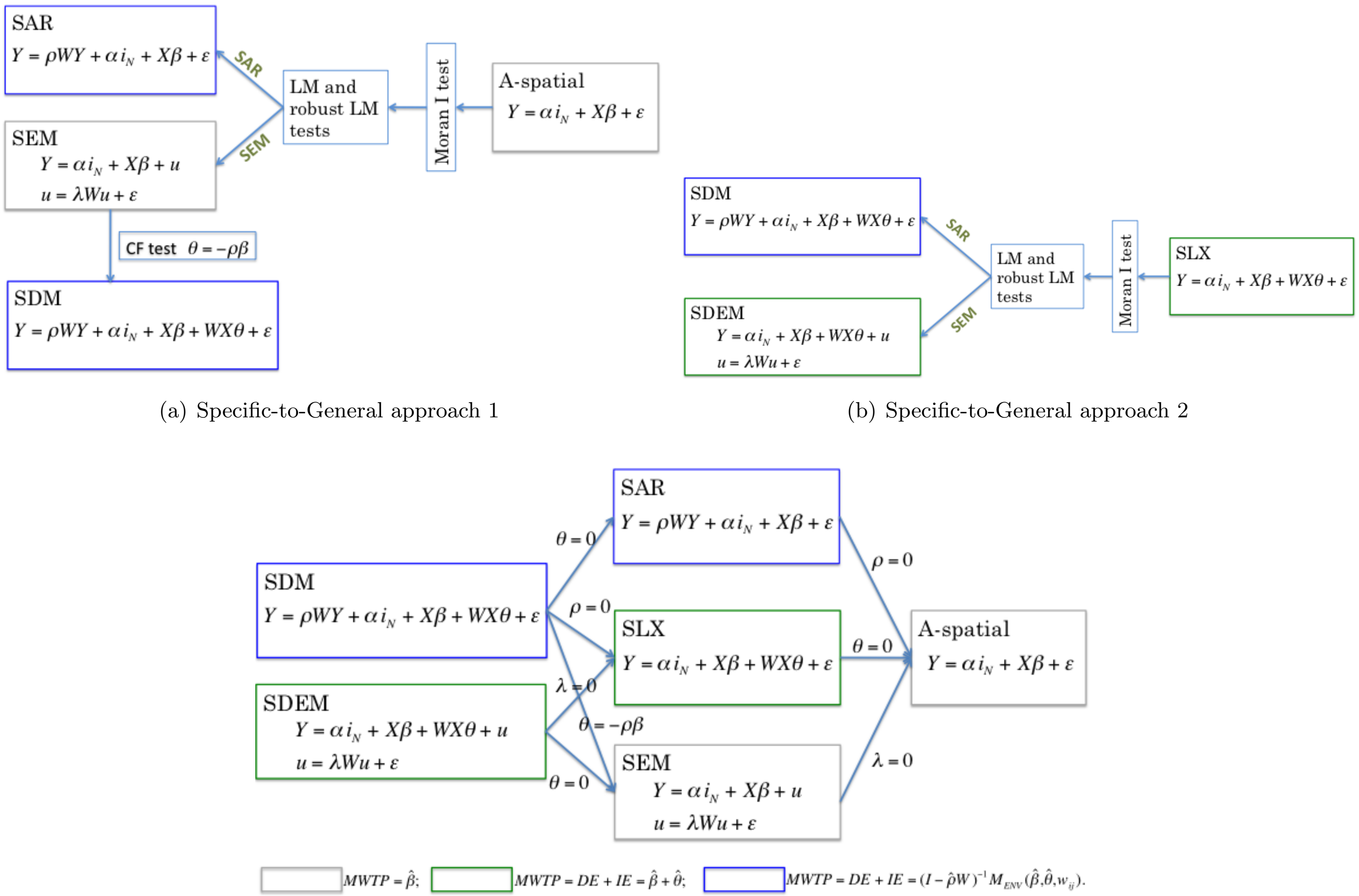


Figure 5: Two approaches of spatial specification selection



(a) Specific-to-General approach 1

(b) Specific-to-General approach 2

(c) General-to-Specific approach

Adapted from Vega and Elhorst (2013)

Figure 6: Implicit prices for Lot size

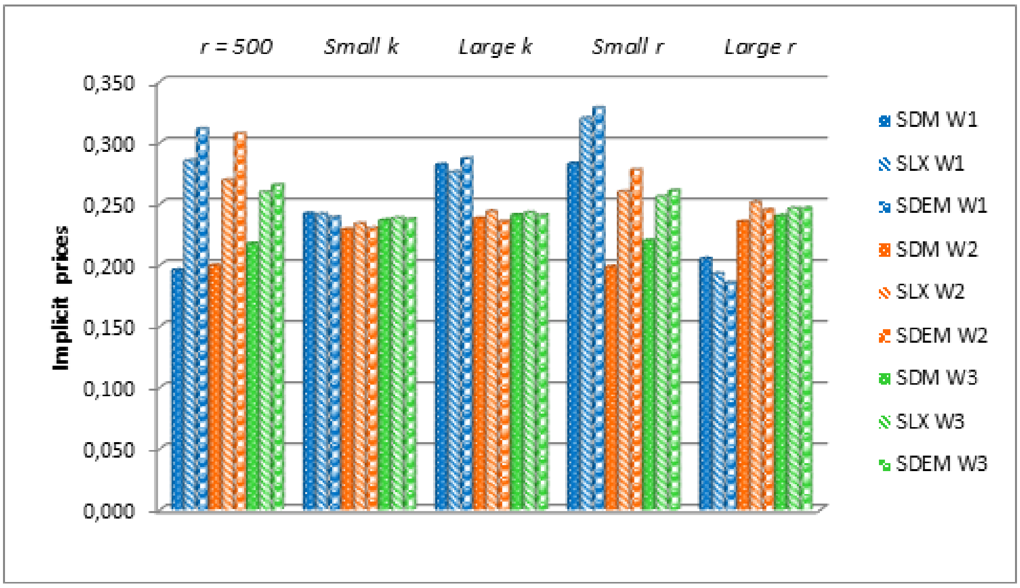


Figure 7: Implicit prices for Rural Housing Developments

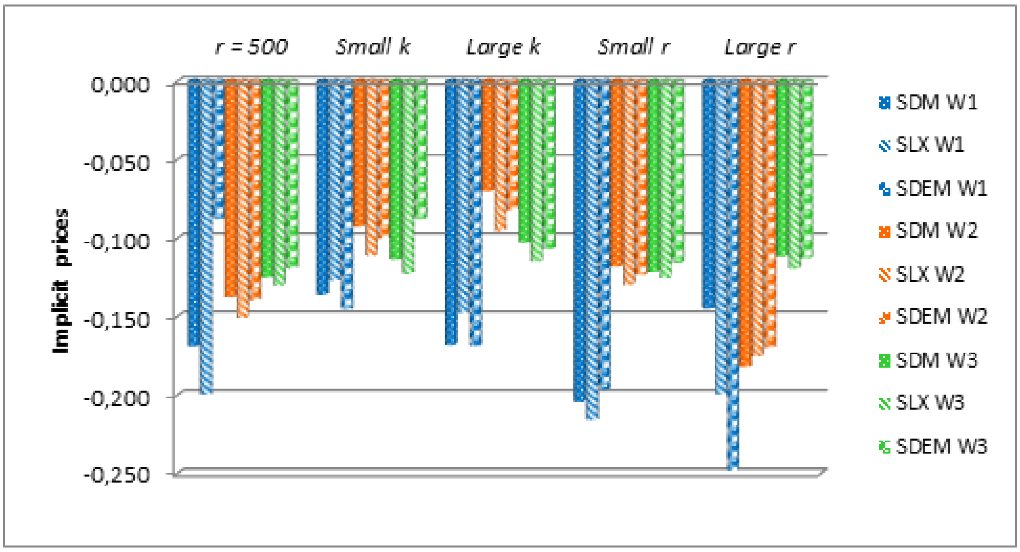


Figure 8: Implicit prices for Rural Isolated Hamlets

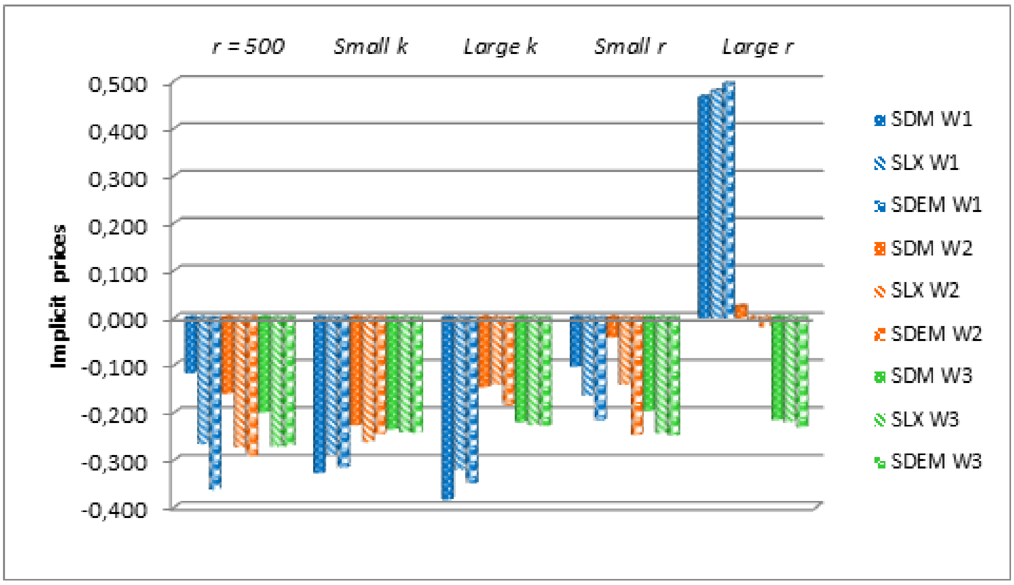


Figure 9: Implicit prices for proximity to secondary rivers and channels

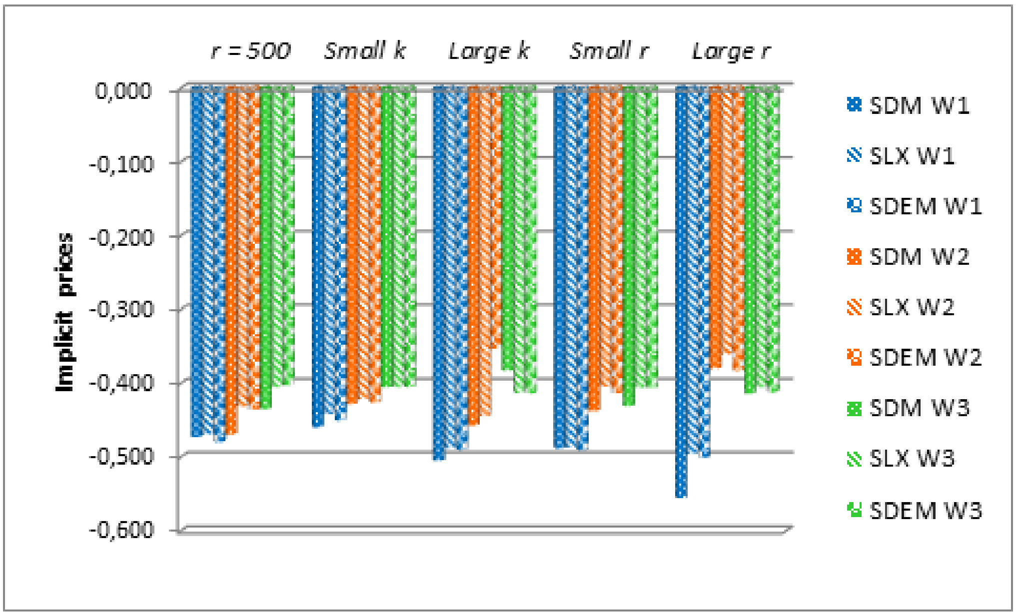


Figure 10: Implicit prices for proximity to wetlands

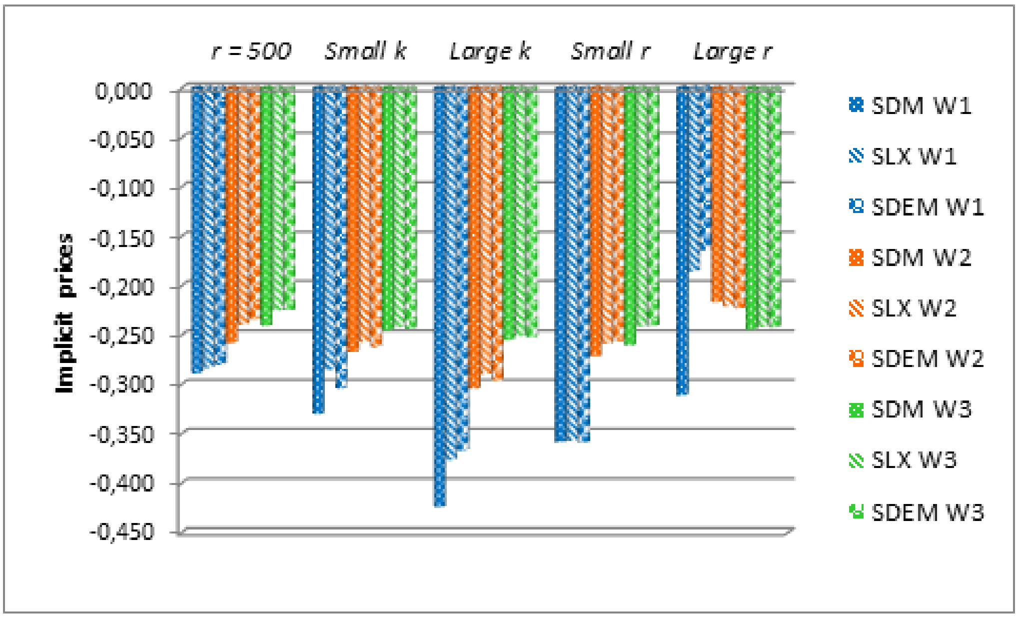
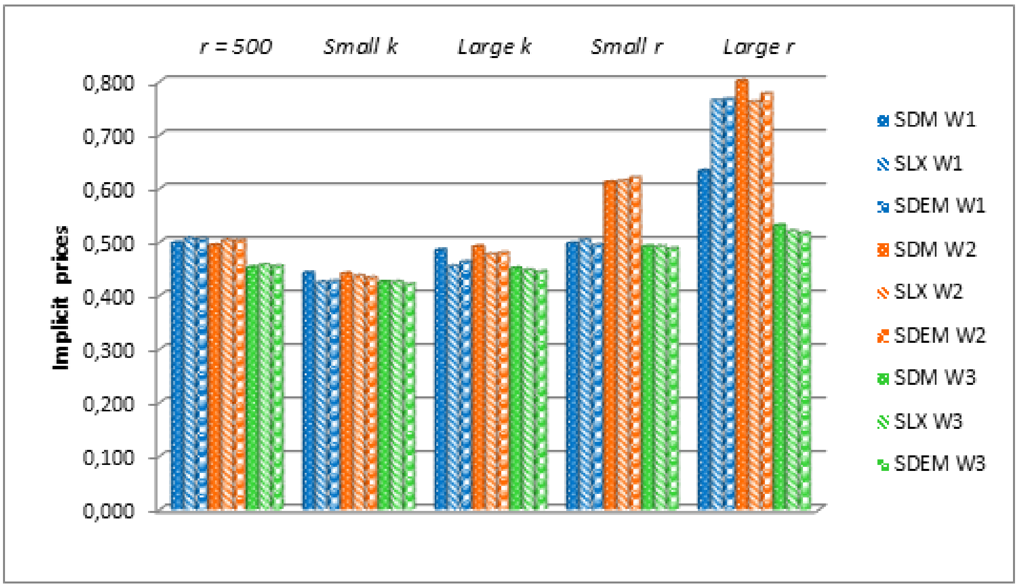
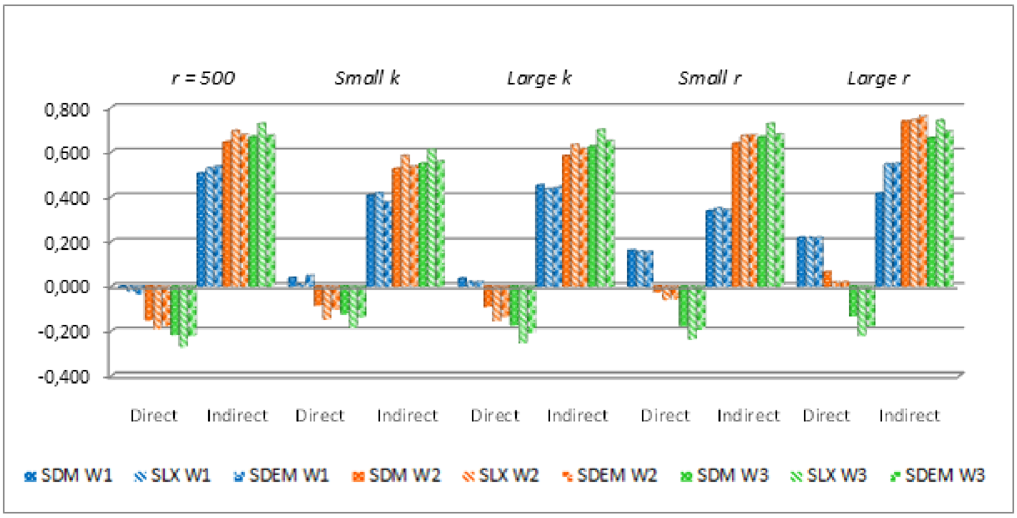


Figure 11: Proximity to seaboard: implicit prices and its spatial propagation

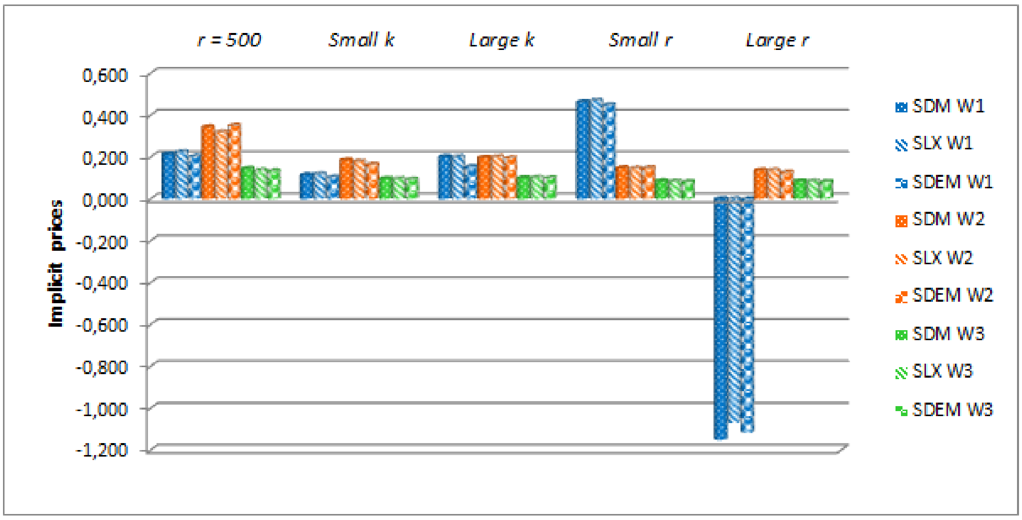


(a) Implicit prices

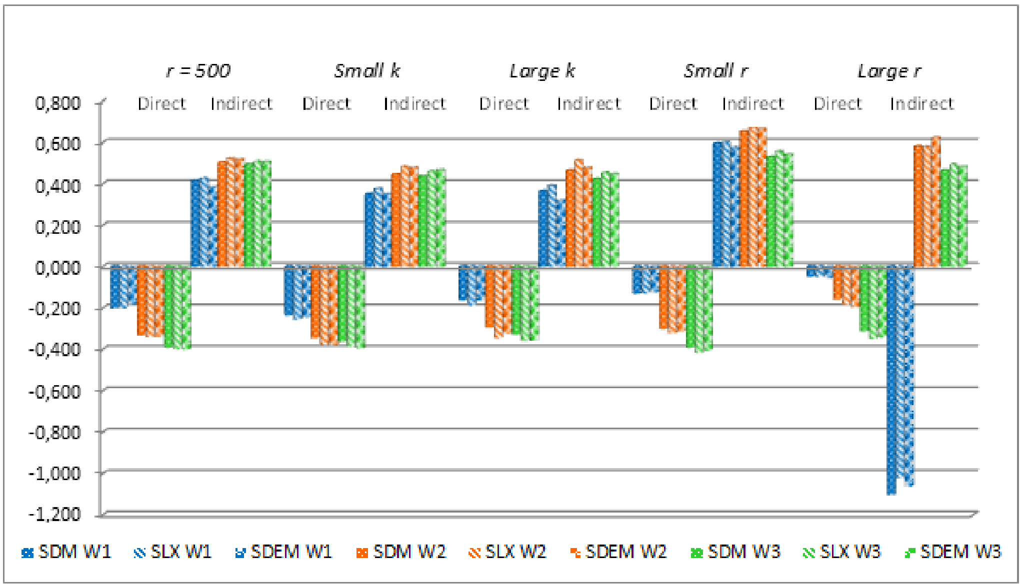


(b) Spatial propagation of the seaboard amenity

Figure 12: Proximity to upper middle noisy roads: implicit prices and its spatial propagation



(a) Implicit prices



(b) Spatial propagation of the noisy road effect

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