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

Nature et impacts des spillovers environnementaux sur les prix des logements: Une analyse hédonique spatiale.

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Abstract

This paper questions the estimation of implicit prices for environmental attributes when spatial dependencies and spatial diffusion processes are present. We use spatial hedonic evaluation methods applied to housing prices. We refer to recent advances in spatial econometrics to show that the marginal willingness to pay for environmental attributes may be interpreted in terms of local or global spillovers. We drive an empirical study in the *Basse Loire* area, a rural and urban area well occupied by several natural spaces and urbanized areas. We study various spatial interaction patterns to test the robustness of our estimates and we find that spatial dependencies based on squared inverse distance and small neighborhoods provide stable estimations. As expected, positive impacts are concentrated on traditional amenities 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 proximity 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.

Keywords : Environmental evaluation, Implicit prices, Housing prices, Spatial hedonic models, Spatial multiplier

JEL classification : Q51, C21, C18

1 Introduction

Environmental evaluation by hedonic housing price models are known as relevant and well developed in empirical literature to assess households' willingness to pay for environmental

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attributes. In recent decades, it addresses a growing variety of topics as the environmental issues develop and relevant data become available. It applies to estimate the demand for air quality (Neil *et al.*, 2007; Yusuf and Resosudarmo, 2009) and for ecosystem services (Ma and Swinton, 2011). It allows to estimate the impact of environmental amenities on housing values such as landscape, view or beach quality (Cavailhes, 2009; Choumert and Travers, 2010; Landry and Hindsley, 2011). It develops to assess the impact of negative externalities on housing values produced by airport or traffic noise (Day *et al.*, 2007; Cohen and Coughlin, 2008), hazardous waste sites (Boxall *et al.*, 2005; Travers *et al.*, 2009), water quality (Cho *et al.*, 2011) or flood risk (Daniel *et al.*, 2009). As spatial hedonic models have became a standard in housing price analysis, environmental evaluation, mainly concerned by geographical factors, has questioned its improvement margins in this framework. According to Bell and Dalton (2007), spatial econometric methods raised a major issue for environmental evaluation to consider spatial dependence effects in housing prices and their explanatory factors. In fact, to control for proximity to environmental amenities or nuisance, even with some distance based measures, doesn't prevent from econometric problems due to spatial dependence which has to be tested (Mueller and Loomis, 2008). Spatial analysis opens also to new understandings of how housing prices capitalize not only the impact of each environmental attributes but are affected through some spatial multiplier effects by an additional impact brought by the spatial distribution of environmental attributes on the area.

Spatial hedonic models have been widely used but without considering this additional environmental effect. Recent contributions in spatial econometrics (LeSage and Pace, 2009) showed that changes the estimation of willingness to pay for environmental attributes. Considering the area of the estuary of the Loire river in France (hereafter named *Basse Loire* area), our aim is to address this question and to contribute to environmental evaluation in three directions. Our estimations of implicit prices for environmental attributes take into account both individual effects and global effects. We first show that the resulting total effect differ from usual results even when spatial models are used. Environmental policies will then be based on incorrect estimates. Considering recent advances in spatial econometrics improves environmental evaluation *per se*. The *Basse Loire* area, as many other regions, concentrates various environmental attributes, associated to natural resources - like ponds, rivers and ocean front - or brought by urbanization like roads and industrial zones. The spatial distribution of these environmental endowments produces *in fine* a global environmental pattern (see the map on the Figure 1) where individual impacts intersect. The estimated total effects take into account a part of these intersections given the interaction pattern W modeled in the spatial hedonic equation. In a way, the individual assignment problem of each effect is overcome without loss for environmental evaluation and this is the second improvement made by our empirical methodology.. Modeling spatial dependencies with a given W interaction pattern often questions the robustness of the results to other spatial interaction patterns. This problem is complicated by the fact that total effects depend on the estimated spatial specification, while the latter is identified by specification search approaches, methods that are themselves likely to be sensitive to the choice of W. Our third improvement is to realize a large robustness analysis either for model selection and spatial interaction designs.

The remainder of the paper is organized as follows. In Section 2, we present our methodological framework. The empirical case study is presented and we discuss the nature of environmental attributes and the type of spatial spillovers that are evaluated by the hedonic methods. Our estimation strategy is detailed in section 3. The spatial interaction patterns are defined and the specification search approaches are presented. Section 4 discusses the results and interpretations for environmental evaluation. The last section gives some concluding remarks and implications for future research.

2 Methodological framework

2.1 Environmental evaluation in the Basse Loire area

According to urban microeconomic models, the housing choice maximizes the residential utility depending on a set of characteristics of the house (H) and a set of attributes (X) associated to its location (Baumont, 2009). The corresponding hedonic equation (1) defines the housing prices P as a function of these attributes, some of them being of environmental concerns X^{env}. The estimated implicit prices (equation 2) are used to assess externalities associated to each environmental attribute x_k^{env}.

$$\mathrm{P} = f(H, X^{env}, X^{others}) \tag{1}$$

$$(MWTP)_k^{env} = \frac{\partial P}{\partial x_k^{env}} \tag{2}$$

Even if housing incorporates some environmental properties (types of heating systems, types of building materials for instance), most of the household's environmental preferences refer to the location choice of the house. Within each country, environmental conditions are omnipresent and their implicit prices may be assess locally - i.e. at the neighborhood scale - or globally - i.e. at the country scale. Neighborhood environmental variables indicate the quality of environmental amenities in the surroundings such as air quality, sound nuisance, open space, scenic views, parks, natural areas, biodiversity... Hedonic evaluation will assess whether or not the housing prices capitalize these local surroundings and will reveal the identification preference of the households, i.e. the type of environmental society where he wants to live. Accessibility variables used to describe households' preferences for accessibility to jobs, goods and services supply within the country, can also describe household's preferences for the accessibility to the market of environmental goods and services located in that country. In that case, hedonic evaluation will assess whether or not housing prices capitalize the proximity to major environmental goods or services (industrial center, airports, major naturel areas, green belt...).

Our empirical model is developed for nine cities in the region known as *Basse Loire*, which covers the estuary of the Loire, an important French river which empties in the Atlantic Ocean near the city of Saint Nazaire. Figure 1 displays the environmental features of the *Basse Loire* area. Our data set combines information on housing and environmental amenities given by two data sources, both available to local administrative jurisdictions: the DIA (*Déclarations d'Intention d'Aliéner*) housing transactions census and GIS data for environmental attributes extracted from land use maps and noise zoning maps. Housing and environmental variables are presented in Table 1 with some descriptive statistics.

The *Basse Loire* is more a suburban and a rural area with a housing stock largely composed of single houses (up to 80% in the rural cities). Then we focus on single family houses and our sample includes 1989 houses sold from January 2004 to December 2006 and plotted on the Figure 1. For each house we collect its price (P) and its size (LOT). To control for the impact of urban centrality, we use a dummy variable ($SNAZ$) to distinguish real estate transactions (20.6% of the sample) located in Saint-Nazaire the main city of the area. Housing Type variable ($TYPE$) is a qualitative variable which proxies 4 homogeneous type of buildings according to a more or less degree of urbanization developments. 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. Larger houses with a garage and larger undeveloped plot are found in the Urban Residential Areas (URA). Rural Housing Development (RHD) indicates a housing development recently built in countryside while 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).

The *Basse Loire* area is largely covered by environmental amenities either natural or more or less anthropized by the process of urbanization (see Figure 1). We define five environmental variables to capture the impact of natural or undeveloped areas including the seaboard (SEA), the Loire river ($LOIRE$), secondary rivers and channels (RIV), wetlands (WET), and ponds ($POND$). If the house is located inside a buffer of 500 meters around the natural amenity, the environmental variable takes the value 1 or 0 otherwise. Almost 60% of the houses are located near wet natural areas (the Loire river, secondary rivers, wetlands or ponds), which underlines the specific environmental value of the estuary area.

The area is also characterized by a high level of industrial activities concentrated in the industrial zone named *Port de Nantes - Saint-Nazaire* with many industries (oil refinery, fertilizer plant and shipyard and aviation plants) listed in the European and French registers of pollutant emissions and/or in the SEVESO classification. The dummy variable ($PORT$) sets whether the house is located closer than 150 meters to this area. Only 7.7% of the sample is concerned by the environmental nuisances (noise, air pollution and ugly landscape). Finally, the *Basse Loire* area is covered by a network of primary and secondary roads and highways. The level of noise induced by the traffic ($NOISE$) is associated to five categories of noise zones: $NOISE1$ ("upper" noisy) to $NOISE4$ ("lower" noisy) and $NOISE0$ (not affected). Almost 30% of the real estate transactions are affected by a noisy road.

2.2 *Spatial effects and environmental hedonic evaluation*

The *Basse Loire* area appears as a spatial organization of various environmental influences pushed by urbanization, economic development and preservation of natural areas. Spatial econometric methods provide useful tools to control for the two spatial dimensions of such spatial patterns: on one hand, the spatial dependences present in the variables - spatial autocorrelation and spatial heterogeneity - and on the other hand, the impact of spatial processes - spatial diffusion and spatial multiplier - underlying to hedonic housing prices models. Recent spatial analysis literature (Elhorst, 2010; LeSage and Pace, 2009; Halleck Vega and Elhorst, 2015) shows that ignoring this second 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. It means that the price of one real estate property is not only affected by its own environmental attributes but it is potentially affected by the spatial distribution of the 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. its implicit price - which potentially involves spatial multiplier effects?

The hedonic property value model is based on the seminal work of 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 (Freeman, 2003; Taylor, 2008).

For the *Basse Loire* area, the hedonic model to be estimated is specified - in the a-spatial specification - by the the log-log equation, which is the most often used in hedonic studies, with the following explanatory variables:

$$\ln P_i =$$
$$\alpha + \underbrace{\beta_1 \ln LOT_i}_{\text{housing attribute}} + \underbrace{\beta_2 SNAZ_i + \beta_3 TYPE_i}_{\text{urban-rural types of buildings}} + \underbrace{\beta_4 SEA_i + \beta_5 LOIRE_i + \beta_6 RIV_i + \beta_7 WET_i + \beta_8 POND_i}_{\text{natural environmental attributes}}$$
$$+ \underbrace{\beta_9 PORT_i + \beta_{10} NOISE_i}_{\text{anthropized environmental attributes}} + \epsilon_i \quad (3)$$

At least five spatial hedonic specifications may be used according to the types of variables that are affected by a spatial process: endogenous variable and/or exogenous variable and/or error terms. The implicit price for environmental attributes adds two effects: a direct effect associated to the observation and an indirect effect coming from neighboring observations. It involves a spatial diffusion process coming from neighbors (local spillover) and may be even more strengthened by a spatial multiplier effect coming from feedback effects across the observations spread over the whole *Basse Loire* area (global spillover). An aggregate measure for all observations is the average of the corresponding terms as suggested by LeSage and Pace (2009). The total value of the implicit price is calculated both with the estimated values of explanatory parameters and the estimated values of spatial parameters. Table 2 presents the main properties of spatial effects and implicit prices for the spatial hedonic equations.

We consider a spatial weight matrix W (more precisely defined in the second part of the paper) to model the spatially lagged variables. The Spatial Error Model (SEM), the Spatial autoregressive model (SAR) and the Spatial Durbin Model (SDM) have been widely used in environmental evaluation.[1] The SEM specification means that the price of a house is affected by the omitted attributes of neighboring houses which vary spatially (Boxall *et al.*, 2005). In that case, spatial dependence is simply a nuisance and the implicit prices are directly given by the estimated values $\hat{\beta}_k$. The SAR model means that the price of one house is affected by the prices of its neighboring houses. The reduced form exhibits a spatial multiplier effect impacting the variables through the inverse spatial transformation $(I - \rho W)^{-1}$. It captures global spillovers coming from the spatial distributions of houses and of their attributes over the whole *Basse Loire* area. The implicit prices are then computed from the estimated values $\hat{\beta}_k$ and the estimated value of the spatial parameter ρ. In the SDM specification there are both endogenous and exogenous interaction effects: the price of each house depends on the price of neighboring houses as well as on the attributes of neighboring houses. The implicit prices for environmental attributes include a local spillover and are globally impacted by the spatial multiplier effects. They are computed from the estimated values $\hat{\beta}_k$, $\hat{\theta}_k$ and the estimated spatial parameter ρ. Finally, Spatial Durbin Error Model (SDEM) and Spatial Lag of Explanatory Variables model (SLX) are two specifications recently used in spatial econometrics. To our best knowledge, the only environmental hedonic study using those specifications is Mihaescu and vom Hofe (2013). In this case, the implicit price of housing attributes is a total effect that adds the estimated values $\hat{\beta}_k$ and the estimated value of $\hat{\theta}_k$.

Spatial diffusion (local spillovers) and spatial multiplier (global spillovers) involved in spatial hedonic models bring additional impacts to include in the estimated value of the implicit price for environmental attribute. It means that household's marginal willingness to pay for environment is not only affected by the environmental endowment of one place but it is also affected by the distribution of environmental endowments on neighboring places and over the whole *Basse Loire* area. These additional impacts depend on the spatial distributions of housing prices and environmental endowments for the observations in the sample. Given the location of houses, they potentially capture multiple sources of environmental amenities that we are not able to distinguish but that we can on the contrary considered as evaluated as a whole. This additional information improves by itself the environmental evaluation. It requires an estimation strategy to define the spatial interaction pattern driving the spatial processes and to identify the spatial hedonic equation to estimate.

[1]See among others, Bell and Bockstael (2000); Anselin and Le Gallo (2006); Osland (2010); Bin *et al.*, 2011; Boxall *et al.*, 2005; Fernandez-Aviles *et al.*, 2012; Wasson *et al.*, 2013; Walsh *et al.*, 2011.

3 Estimation strategy

Technically, to deal with the spatial dimension requires the description of a spatial interaction pattern, defined by the spatial weight matrix W, which indicates the way each observation is connected to each other ones. According to the spatial interaction pattern, a selection process is implemented to discriminate between the various spatial hedonic specifications.

3.1 The spatial interaction patterns

The spatial W matrix defines a spatial interaction pattern to control for spatial dependence effects and to build spatial diffusion processes. It describes for each observation i in the sample which other nearby observations j may be considered as its neighbors - i.e. potentially influence it - and for which level of intensity. For each pairs of observations i and j, the generic term is noted w_{ij}.

In hedonic environmental applications of spatial econometrics models, the most widely used definition for neighbors is based on physical distance between houses (Bell and Bockstael, 2000). We use the Euclidian distance: d_{ij} for each pairs of houses i and j. Defining W matrix gives the answers to the following questions. To what extend do we consider that $w_{ij} \neq 0$ that is i and j interact? Which value can we give to w_{ij}? The first answer allows giving for each house i, its set of neighbors - i.e. its neighborhood. The second answer indicates how the interaction between i and j decreases as d_{ij} increases. The neighborhood is usually defined by a distance threshold $\bar{d}$ (i.e. a given radius r) or by a set of a given number k of nearest neighbors. As r or k gradually increases the size of neighborhoods obviously increases and a non-decreasing number of houses belong to these neighborhoods. The interaction value w_{ij} is usually given either by a binary contiguity index (we denote W_1 the corresponding W matrix) or by the inverse distance (W_2 is the corresponding W matrix) or by the inverse squared distance (W_3 is the corresponding W matrix).

We keep these principles while trying to read them in relation with the *Basse Loire* area and in relation with a virtual behavior on the housing market regarding the information the household needs during his housing research. We consider that two houses i and j are neighbors if d_{ij} does not exceed a given radius r. 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 areas. If we transpose this finding to the household's behavior during his housing search process, it means that more information is collected in central areas than in peripheral ones. For a given radius, "urban" households' get more information than "rural" ones who possibly don't get enough information to drive their choice. On the contrary, the concept of neighborhood based on a given number k of nearest neighbors means that anywhere the household is searching a house, a same amount of information is brought. In dense areas, the k selected houses will be really close while in dispersed areas more distant houses will be selected.

Given a size of neighborhood, either for a distance threshold or for a number of nearest neighbors, what are the implications of the chosen interaction measure? For W_1 the value of interaction is constant and is equal to 1 for each house j belonging to the neighborhood of the house i. In that case, the information sets are equally valued for all the houses located in this neighborhood. For W_2 (respectively W_3) the interaction value (rapidly) decreases for houses j located further in the neighborhood of i. It means that information associated to the closest houses are (even) more valued. As the size of the neighborhood enlarges, even if households look for more information, they are less and less interested by the information associated to more distant houses.

To consider several types of interaction patterns will allow us to conduct a robustness analysis for the environmental evaluation of the *Basse Loire* area.

3.2 Spatial hedonic 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 weaknesses 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 non-spatial equation like the "OLS" model or the SLX model (Table 2) and to test whether a more general model - i.e. including spatial coefficient - is statistically more appropriated (see Figure 2(a)-(b)). To discriminate between the two forms of spatial dependencies - 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). 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 using the estimated values of the parameters as detailed in Table 2.

A *General-to-Specific* approach, discussed for example by Halleck Vega and Elhorst (2015), 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 2(c), is implemented using the LR tests on spatial parameters (ρ, λ or θ). The appropriate specification is then used to calculate the implicit prices of environmental variables (Table 2).

Finally the *"Story"* approach is pushed either by empirical or theoretical arguments. 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 SLX specification helps to capture spatial externalities arising from 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, for all houses located there. Another alternative is to focus on the SEM specification as a correction form for many problems: model miss-specification, omitted variables and measurement errors... With theoretical argument, a spatial specification is drawn from a structural model but for our subject no spatial hedonic specification has been established yet from a structural housing model.

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

4 Estimation results and interpretations for environmental evaluation

4.1 Robustness analysis: neighborhood designs and model choice

For each three types of weights (W_1, W_2 and W_3) we consider an increasing size for the set of connected houses: the radius r increases by steps of 500 meters from 500 meters to 4 000 meters (8 cases), and the number k of nearest neighboring houses increases by steps of 5 new houses from 5 to 50 (10 cases).[2] Fifty four cases are then considered and for each of them we get three sets of results: some descriptive statistics on the sets of the neighbors, the Moran's I statistics for the housing price distribution and the spatial specification equation(s) given by the two specification search approaches. With these results we try to identify if some common trends emerge to reduce the choices among neighborhood designs and spatial specifications to estimate.

Maslianskaïa-Pautrel and Baumont (2015) study the distribution of neighborhoods according to the 54 cases of neighborhood design. The distribution of housing transactions appears spatially concentrated since 75% of the houses have their first nearest neighbors located at 70 meters or less but some observations are distanced from the nearest one by 2 500 meters. Looking at the distance distributions shows also that a neighborhood built with a radius of around 515 meters is similar to the average neighborhood within which a household can find 50 houses to compare with: at least 75% of the 50 nearest neighbors are found within a neighborhood of 543 meters and when a 500 meters radius is exactly considered, the average number of each observation neighbors is 46 with a maximum of 122 neighbors and 21 observations without neighbors. To increase the neighborhood radius rises considerably the average number of neighbors: from 123 for 1 000 meters radius to 653 neighbors for 4 000 meters radius. Such large sets of neighbors are statistically useful to explore whether housing prices remain more or less spatially autocorrelated but they become less relevant for the household's behavior because larger neighborhoods induce more complex process of information gathering.[3] The robustness analysis confirms a local

[2] In order to compare the estimated results, all spatial W matrices have been row standardized.

[3] We show that Moran's I statistics are significant and positive whatever the W matrix used. Moran's I value tends to slightly decrease as the size of neighborhood increases (Maslianskaïa-Pautrel and Baumont, 2015).

process of information research with a neighborhood radius of 500 meters or 45 nearest neighbors. It means that to increase the number of k nearest houses within a small neighborhood brings more detailed information. The interaction pattern based on the inverse squared distance (W_3 spatial weight matrix) appears at least more robust since it produces similar range of results even when large neighborhoods are used: in fact this interaction pattern tends to soften the influence of heterogeneous information brought by more distanced houses.

For those neighborhood configurations, whatever the type of weights, we also obtain fairly close results either for the specification search approaches or for the estimated results.[4]

The two specification search approaches (Specific to General and General to Specific) leads to select the SDM, SLX or SDEM specifications for the neighborhoods based on 500 meters radius (and almost all k nearest neighborhoods). These results may be interpreted as follows: households pay attention to the price of neighboring houses and they don't neglect the exact contribution of the attributes of the neighboring houses brings by the spatial lag of explanatory variables. They are aware of getting detailed information even when they increase their comparison areas. In all cases, neither the a-spatial equation nor the SEM specification has been selected. This implies that the estimated implicit prices of environmental attributes don't reduce to the value of estimated coefficients ($\hat{\beta}_k^{env}$): the implicit prices are correctly obtained by the total effect (which adds a direct effect and an indirect effect). According to the estimated model, this implies to consider $\hat{\beta}_k^{env}$ and $\hat{\theta}_k^{env}$ with a spatial transformation involving $\hat{\rho}$. Then ignoring the spatial dimension in the formation of housing prices leads to inadequate environmental evaluation.

4.2 *Environmental evaluation results*

We only present here the estimated results for the spatial pattern based on W_3 ($r = 500$): inverse squared distance within a neighborhood radius of 500 meters. The Moran's I statistic is equal to 0.404 and is highly significant, confirming a spatial dependence over houses in the study area: high (respectively low) housing values tend to cluster.

OLS estimates and spatial estimates are displayed in Table 3. Let's recall that OLS provides potentially inefficient or biased estimations since it doesn't take into account spatial dependence. For the SDM, SLX and SDEM specifications the implicit prices directly given by the estimated coefficients of explanatory variables is no more correct and has to be computed as a total effect.

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 (LOT). Housing price more precisely increases at a decreasing rate with its lot size since the elasticity is lower than 1. The household is willing to pay around

[4] All results are available upon request from the authors and some details are presented in Maslianskaïa-Pautrel and Baumont (2015).

$2.2 - 2.6\%$ higher for a 10% larger sized lot (Table 3, columns 7, 10 and 13). Do not consider neither spatial effects (OLS, column 2) nor correct estimated values ($\hat{\beta}$ coefficient instead of the total effect) has not a significant modifications on the lot size MWTP.

The residential zoning mainly affects the housing prices through the urban-rural gradient. An house located in the center of the town (TC) is the reference type. Households are willing to pay lower prices to live in rural housing developments (RHD) instead of living in the center of the towns with total effects ranging on average from -0.12 to -0.13. The magnitude of this effect, in terms of elasticity, results in a decreasing value of the house built in rural development programs (RHD) between 11% and 15% compare to the value of a house built in the center of the towns. To live in a rural isolated hamlet (RIH) is even more depreciating with total effects amount from -0.20 to -0.27 which correspond to a depreciation, measured in elasticity, of the property value of about $18 - 24\%$ compared to the center of the town. 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 8 and 10 for SLX model and columns 11 and 13 for SDEM model): -0.214 (-0.206) against -0.130 (-0.119) for rural housing development and -0.323 (-0.321) against -0.271 for rural isolated hamlet. It leads to incorrect bigger estimations of the elasticities of living in a rural housing development or in rural isolated hamlets. In urban areas, living in peripheral residential areas (URA) rather in the center of the towns 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.

We turn now to study the effect of environmental attributes. The proximity to the ocean frontage (SEA) has a positive and significant value with a marginal willingness to pay estimated to 0.452 - 0.457 according to spatial model, which means an elasticity of about 57%. The magnitude of the positive total effect of the seaboard proximity to housing price is consistent to other studies. 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 declines of 36% in moving 500 feet (120 meters) from the Gulf of Mexico. We also underline that ignoring spatial effects leads to a wrong estimation of the elasticity: it is 11% lower with OLS estimation. The decomposition of the total effect between a direct effect and an indirect effect suggests that the marginal willingness to pay for the proximity to the sea is driven by the neighboring houses. Whereas direct effects are negative (about -0.25), indirect effects are strongly positive (vary from 0.668 to 0.727).

The proximity to rivers (RIV) exhibits a strong negative total effect (-0.435 to -0.402) which means elasticities of about -35% to -33% with not significant direct effect and a negative indirect effect. Proximity to wetlands (WET) has also a negative total effect but smaller than for proximity to rivers (from -0.240 to -0.225 which corresponds to elasticities of about -21% to -20%). 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 are located not too close of wetlands in the Minnesota (USA). In our case, the negative impact is supported by the surrounding properties because the indirect effect is negative whereas the direct effect is 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, the implicit price estimated value must not be given by the beta coefficient which is rather false and not significant.

Concerning the noise zones, our results indicate that only a location in the area of upper middle noisy road ($NOISE2$) has a significant impact. This total effect is positive (0.102 to 0.107 corresponding to elasticities about $10.7-11.3\%$) passing through a negative direct effect and a positive indirect effect both significant. In fact, spatial hedonic models capture a significant and positive effect whereas the OLS estimation fails to value it. If we don't implement the spatial transformation to the beta coefficient we come to the wrong conclusion in favor of a strong nuisance which decreases the housing price by 31% (OLS estimation). Conversely, the positive total effect reveals that households balance between nuisance and accessibility as showed by the decomposition between the direct and indirect effects. 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, the proximity to the industrial port zone ($PORT$), with a negative and significant impact in the OLS case, is no more significant once spatial dependence is taking into account.

5 Conclusion

The objective of the paper was to show how the estimation of implicit prices for environmental attributes may be improved when spatial interactions and spatial processes - spatial diffusion and spatial multiplier - are considered in hedonic models. Implicit prices add two effects - one derived from each observation and the other one coming from neighboring observations - which have to be computed both with the estimated coefficients and the estimated spatial parameters of the spatial specification. 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 the 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 integrate flood risks. Robustness analyses have been implemented to select the appropriate spatial hedonic equation with several types of spatial interaction patterns. We observed that spatial interaction patterns based on inverse squared 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. 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.

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Table 1: 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 2: Implicit price of environmental attribute in different spatial models

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

Note: $\hat{\beta}_k^{env}$ and $\hat{\theta}_k^{env}$ denote the coefficients of the corresponding environmental variable x_k^{env}.

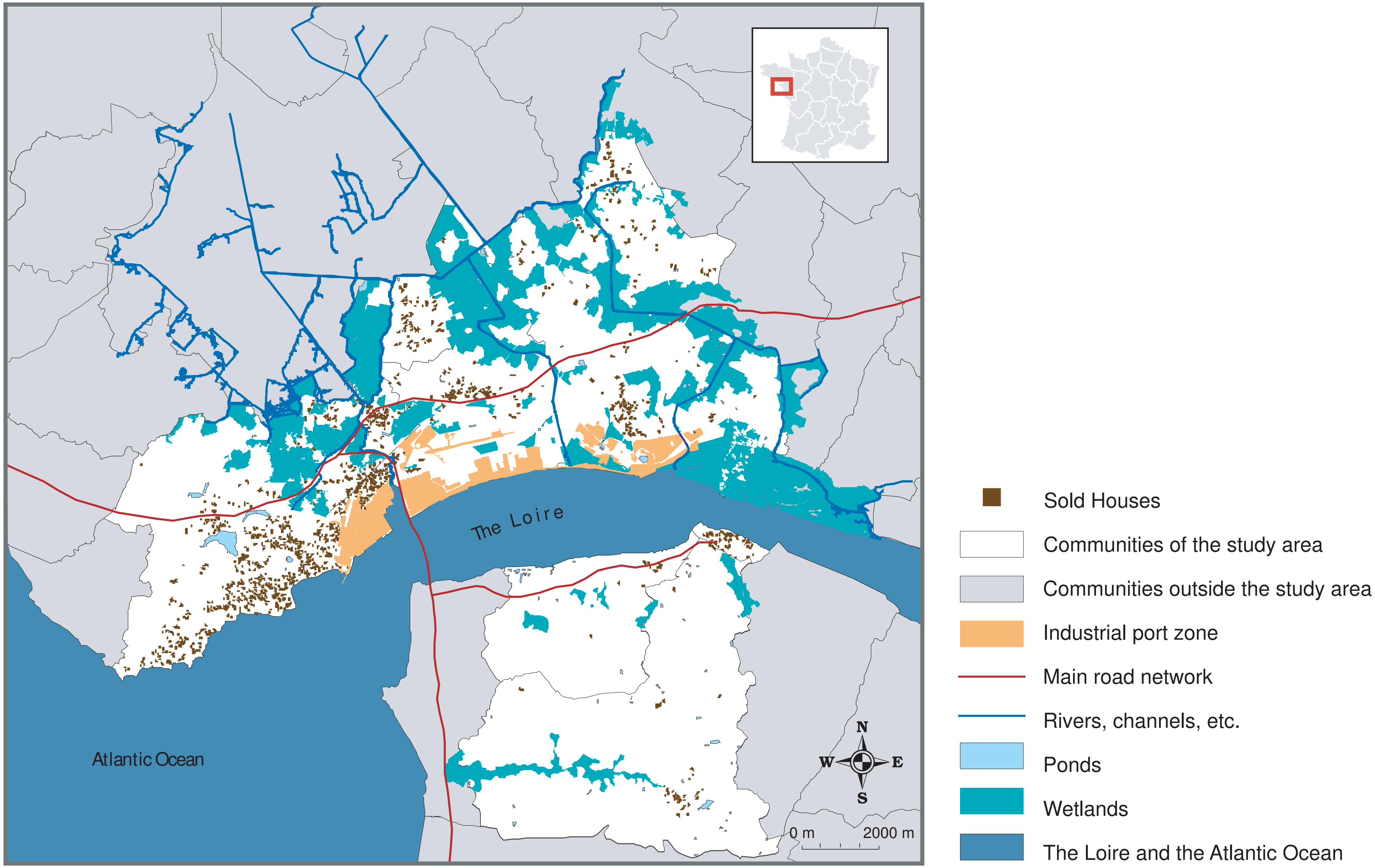
The nature of spatial dependence and spatial effects follows the taxonomy in Anselin (2003) and Halleck Vega and Elhorst (2015). First, we consider whether the spatial correlation in the reduced form pertains only to un-modeled effects (error terms), to modeled effects (included explanatory variables),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

Table 3: Implicit price estimates from hedonic specification

Variable	OLS	Spatial Hedonic with 500 meters neighborhood radius and spatial inverse squared distance matrix (W_3) SDM Model					SLX Model			SDEM Model		
(1)	(2) $\hat{\beta}$ (Elasticity)	(3) $\hat{\beta}$	(4) $\hat{\theta}$	(5) DE	(6) IE	(7) TE (6)+(7) (Elasticity)	(8) DE $\hat{\beta}$	(9) IE $\hat{\theta}$	(10) TE (9)+(10) (Elasticity)	(11) DE $\hat{\beta}$	(12) IE $\hat{\theta}$	(13) TE (12)+(13) (Elasticity)
Housing attributes												
LOT	0.249^{***}	0.274^{***}	-0.009^{**}	0.277^{***}	-0.060	0.217^{***}	0.240^{***}	-0.019	0.259^{***}	0.246^{***}	0.019	0.264^{***}
SNAZ	0.085^{**}	0.008	-0.004	0.084	-0.030	0.053	0.101	-0.026	0.075	0.057	0.028	0.085
TYPE_URA	-0.018	0.009	0.091	-0.087	0.004	-0.046	-0.046	0.042	-0.004	-0.0455	0.0451	-0.0004
TYPE_RHD	-0.138^{***} ($e = -12.9\%$)	0.008	-0.193	0.075	-0.201	-0.125^{*} ($e = -11.8\%$)	$-0.214.$	0.083	$-0.130.$ ($e = -15.5\%$)	$-0.206.$	0.087	$-0.119.$ ($e = -11.2\%$)
TYPE_RIH	-0.297^{***} ($e = -25.7\%$)	0.046	-0.223	0.039	-0.238	$-0.199.$ ($e = -18.0\%$)	-0.323^{*}	0.052	-0.271^{*} ($e = -23.7\%$)	-0.321^{*}	0.050	-0.271^{*} ($e = -23.7\%$)
Environmental variables (natural resources)												
SEA	0.383^{***} ($e = 46.7\%$)	-0.237^{*}	0.639^{***}	$-0.216.$	0.668^{***}	0.452^{***} ($e = 57.1\%$)	-0.270^{*}	0.727^{***}	0.457^{***} ($e = 57,9\%$)	$-0.221.$	0.675^{***}	0.454^{***} ($e = 57.5\%$)
LOIRE	0.092.	-0.005	-0.004	-0.051	-0.049	-0.099	-0.061	-0.006	-0.067	-0.056	-0.001	-0.057
RIV	-0.388^{***} ($e = -32.2\%$)	-0.001	-0.387^{**}	-0.013	-0.421^{**}	-0.435^{***} ($e = -35.3\%$)	-0.089	-0.316^{**}	-0.405^{**} ($e = -33.3\%$)	-0.099	-0.303^{**}	-0.402^{***} ($e = 33.1\%$)
WET	-0.234^{***} ($e = -20.9\%$)	0.002	-0.190^{*}	-0.030	-0.210^{*}	-0.240^{***} ($e = -21.9\%$)	-0.080	$-0.145.$	$-0.225.$ ($e = -20.1\%$)	-0.099	-0.125	-0.224
POND	0.049	0.113	-0.009	0.111	-0.089	0.022	0.077	-0.034	0.043	0.085	-0.048	0.037
Environmental variables (anthropized)												
PORT	$-0.103.$	-0.151	0.005	-0.150	0.040	-0.110	-0.155	0.080	-0.075	-0.158	0.087	-0.071
NOISE1	-0.027	-0.001	-0.001	-0.008	-0.015	-0.023	0.002	-0.018	-0.016	-0.027	0.013	-0.014
NOISE2	0.019	-0.406^{**}	0.497^{***}	-0.391^{**}	0.493**	0.102. ($e = 10.7\%$)	-0.399^{**}	0.506^{**}	0.107^{**} ($e = 11.3\%$)	-0.400^{**}	0.505^{***}	0.105^{**} ($e = 11.1\%$)
NOISE3	$-0.059.$	-0.008	0.002	-0.077	0.012	-0.065	-0.093	0.032	-0.061	-0.100	0.049	-0.051
NOISE4	0.058	0.003	0.001	0.032	0.019	0.051	0.038	0.027	0.065	0.036	0.026	0.062
Adj. R^2	0.28											
ρ		0.110^{***}										
λ										0.212^{***}		
Res.St Error	0.47	0.46					0.47			0.45		

Notes: Number of observations 1 989. Elasticities are given for significant discrete variables
DE - direct effect, IE - indirect effect, TE - total effect
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.

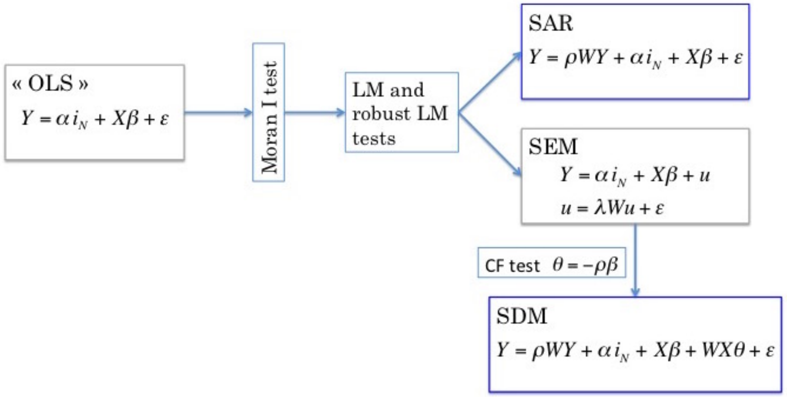
Figure 1: *Basse-Loire* study area



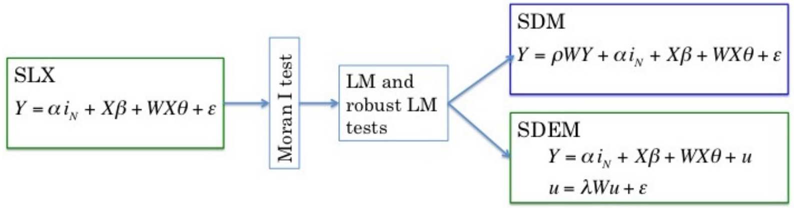
Design: *Masha Pautrel*; Construction: *Claire Choblet, Masha Pautrel*

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.

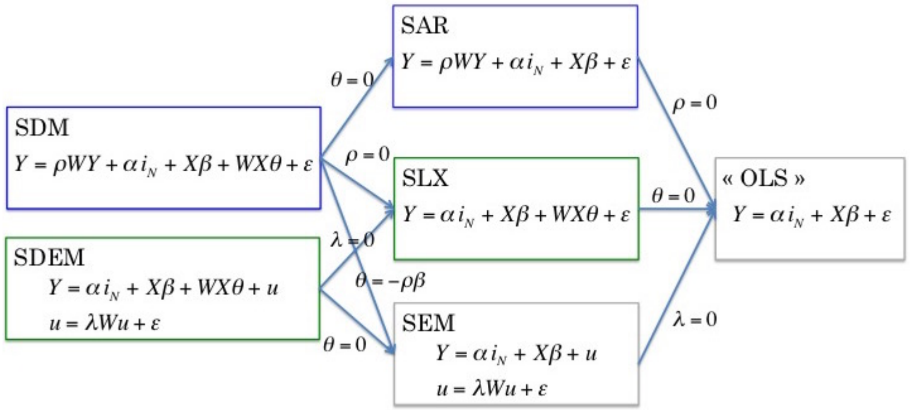
Figure 2: Two approaches of spatial specification selection



(a) Specific-to-General approach 1



(b) Specific-to-General approach 2



(c) General-to-Specific approach

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

Adapted from Halleck Vega and Elhorst (2015)