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Spatial Heterogeneity of Sustainable Transportation Offer Values: A Comparative Analysis of Nantes Urban and Periurban/Rural Areas (France)

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Abstract: Innovative solutions have been implemented to promote sustainable mobility in urban areas. In the Nantes area (northwestern part of France), alternatives to single-occupant car use have increased in the past few years. In the urban area, there is an efficient public transport supply, including tramways and a "busway" (Bus Rapid Transit), as well as bike-sharing services. In periurban and rural areas, there are carpool areas, regional buses and the new "tram-train" lines. In this article, we focus on the impact on house prices of these "sustainable" transportation infrastructures and policies, in order to evaluate their values. The implicit price of these sustainable transport offers was estimated through hedonic price functions describing the Nantes urban and periurban/rural housing markets. Spatial regression models (SAR, SEM, SDM and GWR) were carried out to capture the effect of both spatial autocorrelation and spatial heterogeneity. The results show patterns of spatial heterogeneity of transportation offer implicit prices at two scales: (i) between urban and periurban/rural areas, as well as (ii) within each territory. In the urban area, the distance to such offers was significantly associated with house prices. These associations varied by type of transportation system (positive for tramway and railway stations and negative for bike-sharing stations). In periurban and rural areas, having a carpool area in a 1500-m buffer around the home was negatively associated with house prices, while having a regional bus station in a 500-m buffer was non-significant. Distance to the nearest railway station was negatively associated with house prices. These findings provide research avenues to help public policy-makers promote sustainable mobility and pave the way for more locally targeted interventions.

Keywords: sustainable mobility; transport accessibility; geographically weighted regression; hedonic pricing method; spatial dependence; spatial heterogeneity

1. Introduction

To become a sustainable city or, more broadly, to develop a sustainable territory, has become a major challenge of our societies. Rethinking the organization of our cities, and thus changing the traditional planning models, is one of the priorities of public policies [1]. This involves promoting sustainable infrastructures and especially offering alternatives to the single-occupant car. In France in 2014, the transport sector was considered the main source of greenhouse gas emissions, representing slightly less than 30% of the national emissions. Moreover, these transport-related emissions increased significantly (+20%) between 1990 and 2001 [2]. Concerning the local pollution, most air pollutants were related to human activity. For example, in France in 2015, the transport sector was responsible for 61% of NOx emissions, 8% of non-methane volatile organic compound (VOC) emissions, 14% of PM10 particles and 18% of PM2.5 particles [3]. Whatever the scale, from local to global, public actions are developed in terms of sustainability, with the transport sector being no exception [4]. Transport policies should meet sustainability goals and encourage changes in single-occupant car user behaviors. With this aim, innovative solutions have been implemented to promote sustainable mobility in urban areas, limit the impact of single-occupant cars, reduce the transport budget of households and facilitate travel. Such solutions, which have emerged over the past fifteen years in France and Europe, encompass bike-sharing schemes (e.g., Velib' in Paris), different forms of car sharing such as "self-service" electric cars (e.g., Autolib' in Paris or Zipcar in a few US cities), platforms dedicated to carpooling, "green" public transport, and so on.

Transport infrastructure has always been a key determinant of land use evolution and real estate prices are a significant measure reflecting these changes [5–8]. In this study, we aim to evaluate the economic value of a sustainable transport infrastructure through a hedonic approach, which has previously been used to assess the economic value of environmental goods such as landscape quality, noise, air and water pollution [9]. According to Rosen [10]—the instigator of the hedonic pricing model—real estate prices depend in part on proximity to public transport and amenities and sources of pollution. The real estate market indirectly provides the monetary value of these attributes through the observed difference between the values of two goods, identical in every respect with the exception of one of the characteristics studied. This difference in value is due to the gain or loss in wellbeing that buyers attribute to the proximity of a transport service, an amenity or a nuisance related to air quality or the noise exposure level. In this article, we focus only on "sustainable" transport infrastructures. The hedonic price method has been extensively studied worldwide to evaluate transport infrastructures, including public transport (see the next section). The originality of our research is threefold:

i. it evaluates the value of alternatives to single-occupant car use in both urban and periurban/rural areas;
ii. it looks at the spatial heterogeneity of these values within each subarea;
iii. it considers original transport infrastructures in such types of analyses (hedonic price method), namely carpool areas in periurban/rural areas and a bike-sharing system in an urban area.

To achieve these goals, we used the hedonic price method as defined above and the techniques of spatial econometrics and local analyses. The main aim of the analysis was to assess the impact of a sustainable transportation infrastructure on the property sale price in order to provide useful elements to help policy-makers reduce single-occupant car use. Section 2 is dedicated to the literature review. Section 3 presents the theoretical econometric models. Section 4 describes the study area and the data. Section 5 presents the calibration of the models. Section 6 focuses on the results of the econometric models and Section 7 discusses the results. Finally, we highlight that, in Nantes Métropole, proximity to alternative offers to the private car has a direct and mainly positive impact on house prices, whereas in periurban/rural areas this effect is either minor or nonexistent. We reveal a territorial heterogeneity, which implies an adaptation of transport policies and therefore different solutions to achieve sustainable mobility throughout the territory.

2. Literature Review

The relationship between house prices and transport infrastructure is a popular research topic. The impact of transport infrastructure proximity (such as light rail or subway stations and railways) on dwellings has been explored in many studies. In France, the property value due to accessibility to public transport was highlighted by Beckerich [11] in Lyon, Fritsch [12] in Nantes, and Boucq and Papon [13] and Nguyen Luong and Boucq [14] in the Paris region. In other European countries, the results of Martinez and Viegas [15] in Lisbon (Portugal) suggested that proximity to one or two metro lines led to significant property value changes. In Athens (Greece), metro, tram, suburban railway and bus stations affected dwelling prices positively, while ISAP (the old urban railway of Attica) and national rail stations, airports and ports had a negative effect due to a number of externalities associated with them, such as noise [7]. In the United States, Bowes and Ihlanfeldt [16] found both positive and negative effects of rail stations on the local house prices in Atlanta. Several other studies conducted in the USA showed a positive relationship between property values and the distance from light rail (LRT) stations, such as in Santa Clara (California) [17,18], Charlotte (North Carolina) [6], Buffalo (New York) [19], Dallas (Texas) [20], Portland (Oregon) [21] and Phoenix (Arizona) [22]. In Brisbane (Australia), Mulley et al. [23] found that being close to a bus rapid transit (BRT) added a premium to the housing price of 0.14% for every hundred meters closer to the BRT station. In Shanghai, the hedonic price modeling of Pan and Zhang [24] showed that the transit proximity premium amounted to approximately 152 yuan/m^2 (about 20 €/m^2) for every 100 m closer to a metro station, and Li et al. [25] found similar results in Beijing. Chen and Haynes [26] reported a strong positive effect of the Beijing-Shanghai high-speed rail line on housing values, especially in small and medium cities. In Singapore, Diao et al. [8] found that the opening of an LRT increased housing values within the 600 m network distance from the new stations.

Some studies have also explored the relationship between bike facilities and house price. For instance, Liu and Shi [27] underlined that the density of the bike network in Portland (Oregon) was a positive contributor to property values. Welch et al. [21], however, found more mixed results in the same city. In Montreal (Canada), El-Geneidy et al. [28] highlighted that the presence of a bicycle-sharing system in a neighborhood with 12 stations serving an 800-m buffer was expected to increase property values by approximately 2.7%. A summary of these literature findings is presented in Table S1.

3. Presentation of the Econometric Models

3.1. Hedonic Price Model

The objective of the hedonic price method is to reveal the implicit prices of the different attributes of a heterogeneous good on the basis of its overall price. The study of Lancaster [29] laid the theoretical foundations of this method and Rosen [10] formalized it. Rosen proposed a two-stage method in which each stage has limitations that should not be overlooked in an econometric approach. The most common problems are: (i) the failure to take into account the expectations of future levels of amenities [30]; (ii) the endogeneity of certain explanatory variables, which leads to them being not exogenous and correlated with the regression residuals. The OLS estimates then give biased and non-convergent results [31]. The method of instrumental variables makes it possible to remedy them, and is used in the works of Bartik [31] and Cheshire and Sheppard [32]; and (iii) spatial heterogeneity (variation in housing characteristics and prices across space) and spatial dependence (dependence of the housing characteristics and prices in one place on the characteristics of neighboring places). These problems have been highlighted and addressed in many works (e.g., [33,34]).

3.2. Spatial Models

The geolocalized data, i.e., the data for which each observation is associated with a location identified by its geographical coordinates (postal addresses of the transactions in our study), require special treatment [34]. Spatial observations are frequently interdependent: what happens in a particular location depends on what happens in other locations and refers to the so-called spatial dependence [33]. Real estate transactions are no exception. Spatial econometric methods use an instrument to represent these spatial interactions, namely the weight matrix (W) or matrix of the neighbor location data points. With N observations, we use a square matrix W ($N \times N$), whose diagonal terms are zero and whose non-diagonal term w_{ij} becomes higher as the effect of observation j on observation i becomes larger [35]. These matrices are based on either contiguity or distance and are then used to create spatially lagged variables, applicable to the dependent variable, the independent ones, or the error term [7]. These weight matrices can also be based on networks [36]. Specifications of the model calibration are given in Section 5.

The spatial econometric model aims are presented as follows:

(1) Spatial AutoRegressive Model (SAR) [37]:

$$Y = \rho WY + X\beta + \varepsilon \quad (1)$$

where Y is the variable explained, X is the matrix of the exogenous variables, ε is an error term, and β is the vector of regression coefficients. The SAR model accounts for a spatial dependence on the endogenous variable: the price of the house sold (Y) depends on the prices of neighboring houses, ρ being the spatial parameter to be estimated.

(2) Spatial Error Model (SEM) [37]:

$$Y = X\beta + \varepsilon \text{ with } \varepsilon = \lambda W\varepsilon + \mu \quad (2)$$

where Y is the variable explained, X is the matrix of the exogenous variables, ε is an error term, and β is the vector of regression coefficients. The SEM model is specified with an autoregressive structure of the error term, where λ is the spatial parameter to be estimated.

(3) Spatial Durbin Model (SDM) [37]:

$$Y = \rho WY + X\beta + \gamma WX + \varepsilon \quad (3)$$

The SDM model combines the dependence effects on the explanatory variables and on the endogenous variable. The spatial autoregressive process is applied to both the explained and explanatory variables. ρ and γ are the spatial parameters to be estimated. This model can potentially remove the bias caused by the omitted variables.

(4) Geographically Weighted Regression (GWR) [38]:

$$y_i = \beta_0(u_i, v_i) + \sum_k \beta_k(u_i, v_i)X_{ik} + \varepsilon_i \quad (4)$$

where (u_i,v_i) represents the geographical coordinates of location i. The GWR model aims to detect the spatial heterogeneity of statistical relationships by exhibiting the spatial patterning of local regression coefficients. It extends the traditional regression framework by allowing coefficients to vary throughout space. One weighted regression is performed per data point, according to a spatial weighting scheme giving more importance to nearer neighbors than farther ones. A key point of the GWR model is therefore to calibrate an appropriate kernel function (see Section 5).

4. Study Area and Database

4.1. Nantes Urban and Periurban/Rural Areas

The objective of this study was to evaluate sustainable transport solutions in the whole Nantes region (Figure 1), which had 940,000 inhabitants within 114 municipalities in 2012. In order to distinguish spatial contexts, the study area was divided into two samples, according to the administrative boundaries: (i) the urban area, corresponding to the intercommunal administrative entity centered on the city of Nantes and called Nantes Métropole (619,000 inhabitants in 24 cooperating municipalities) and (ii) the periurban and rural areas (321,000 inhabitants in the 90 remaining municipalities of the Nantes region). In fact, the alternatives to single-occupant car use differ according to the location, i.e., urban or less dense territories. This is partly due to the specific local authorities in charge of different transportation networks depending on the type of territory. These networks are expected to meet the needs of various mobility users living in heterogeneous geographical contexts.

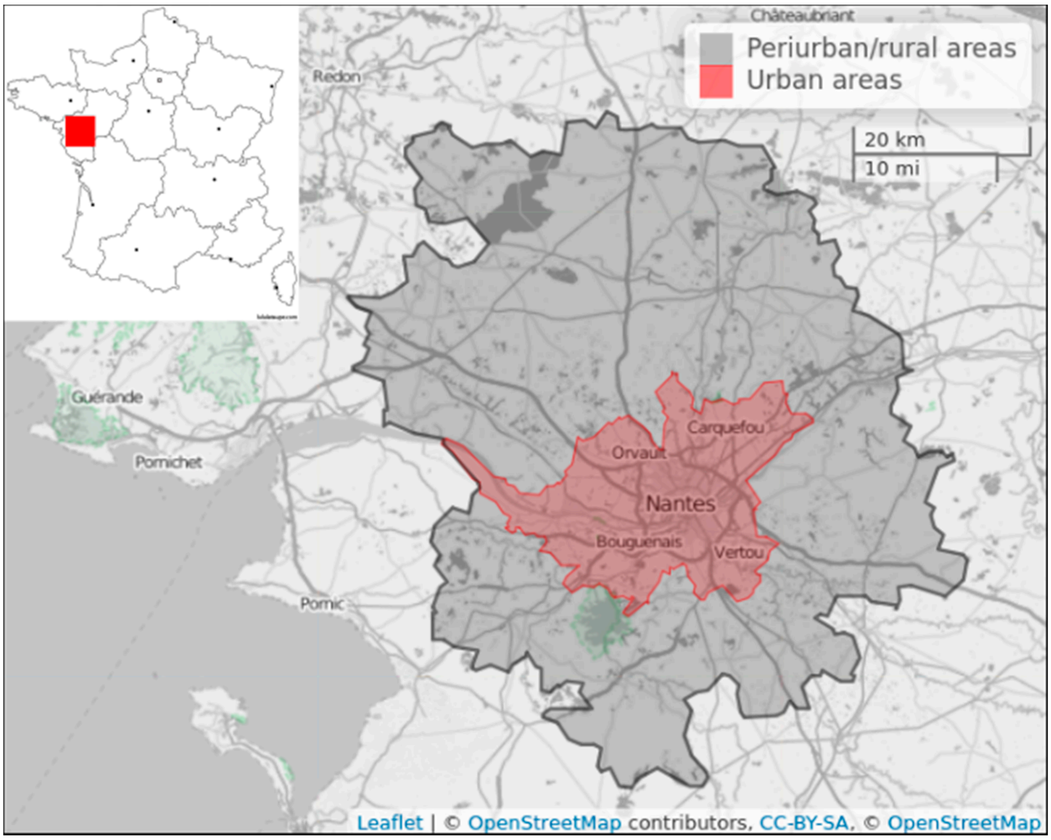

Figure 1. Location map.

Our study concerned 2262 house transactions, including 1353 in the urban area (Nantes Métropole) and 909 in the periurban and rural areas. In the Nantes urban area (Nantes Métropole), three transportation networks or mobility offers are of interest (Figure 2). The first concerns the location of the 11 railway stations that were in service in 2012. We added the 5 railway stations in the northern part of the urban area (the "tram-train" line from Nantes to Châteaubriant, located 70 km north of Nantes). This specific transport line was opened in February 2014 and was planned by the regional public authority long before 2012; this is why it seemed reasonable to consider that potential accessibility gains provided by this new transport offer could be evaluated in housing prices at this time [39]. The four tramlines were constructed to facilitate radial trips towards Nantes city center using public transport from the rest of the urban area. The first three lines were implemented between 1985 and 2000 while the fourth one (the "busway", a Bus Rapid Transit or BRT line) was put into service in 2006 as part of the 2000–2010 Urban Transport Plan. The "Bicloo" bike-sharing offer was provided in the central districts of the Nantes urban area in 2008. The station network was gradually extended over a wider territory and included 103 stations in 2012.

The other transportation networks or mobility offers are implemented at the scale of the periurban/rural areas as well as in the Nantes urban area (Figure 2). This is the case of the railway stations along the five train lines leaving Nantes. Many "Lila" bus stations have been implemented in the whole *département* and within the periurban and rural areas (n = 435). Finally, carpool stations have been either implemented or authorized since 2009 thanks to the contribution of the Loire-Atlantique *département*.

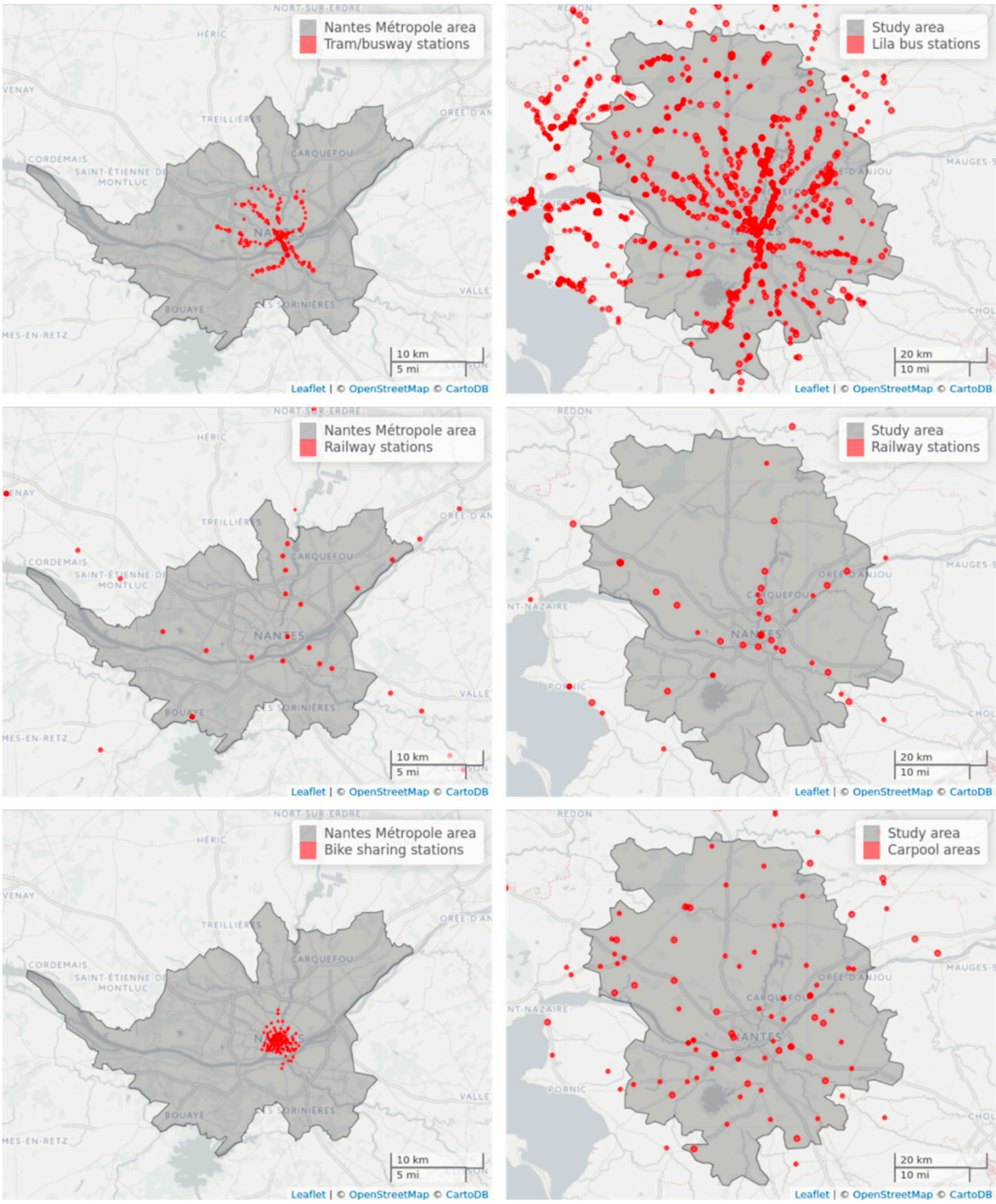

Figure 2. Sustainable transport infrastructure and study areas.

4.2. House-Related Variables

Our analysis focused on the houses that changed hands in 2012. The sale prices and the various intrinsic characteristics of the houses (living surface area, construction period, etc.) came from the PERVAL notarial database. The variable explained is the 2012 sale price in €. Table 1 presents the intrinsic and other variables used in the study.

Table 1. List and descriptive statistics of the variables used in this study.

Variables	Definition	URBAN Area Mean or % (Std.)	Periurban/Rural Area Mean or % (Std.)
House price in €	Dependent variable	272,031 (122,070)	188,566 (85,865)
Intrinsic Variables			
Living surface area (m^2)	Living space in square meters entered in the deed	104.96 (27.7)	104.46 (26.5)
Land surface area (m^2)	Total area of land in square meters, corresponding to the cadastral area	1143.9 (4057.6)	1583.33 (4260.3)
Construction period	When the house was built, with 7 different classes:		
	A: <1913	5.1	11.2
	B: 1914–1947	15.4	20.2
	C: 1948–1969	19.4	11.2
	D: 1970–1980	24.2	18.4
	E: 1981–1991	14.2	8.3
	F: 1992–2000	8.7	6.7
	G: 2001–2012: the reference variable	13.0	24.0
Neighborhood Variables			
Population density (inhabitants/km^2)	Population density (inhabitants/km^2) at the IRIS scale	3003.9 (2553.0)	196.6 (257.8)
Unemployment rate (%)	Unemployment rate at the IRIS scale	9.9 (3.8)	7.8 (1.8)
Social diversity index	Diversity index (from 0 to 1) at the IRIS scale based on 6 socio-professional classes. A value of 1 indicates an identical distribution of the 6 classes in the IRIS.	0.82 (0.03)	0.86 (0.03)
School	Distance to the nearest primary or high school	540.4 (537.8)	1150.1 (1054.1)
Parks	Distance to the nearest park	398.8 (300.5)	1270.8 (1240.9)
Shopping center	Distance to the nearest shopping center	994.5 (749.8)	2953.6 (2337.5)
Transport Infrastructure Variables			
Railway station	Distance to the nearest railway station	2288 (1397)	6984 (5304)
Tram or busway station	Distance to the nearest tram or busway station	2358 (2353)	n/a
Bike-sharing station	Distance to the nearest bike-sharing station	4363 (3435)	n/a
"Lila" bus station	At least one "Lila" bus station in a buffer of 500 m radius near the house. It is a dummy variable, 1 if <500	n/a	0.45 (0.5)
Carpool area	At least one carpool area in a buffer of 1500 m radius near the house. It is a dummy variable, 1 if <1500 m	n/a	0.34 (0.48)

4.3. Spatial Variables

Since the neighborhood characteristics where the dwelling is located might also influence the sale price, six contextual variables related to the socioeconomic environment and the built environment were added to the models: population density (inhabitants/km^2), unemployment rate (%) and a social diversity index were assessed at the IRIS Census unit scale. The IRIS areas (acronym for "Aggregated Units for Statistical Information") are provided by the French National Institute of Statistics and Economic Studies (INSEE, www.insee.fr); they represent the smallest unit for dissemination of French infra-municipal data. The social diversity index is a measure of the evenness of distribution of the percentages of six main INSEE-based socio-professional classes (farmers, artisans, managers and higher intellectual professions, intermediate occupations, low-grade white collars, blue collars) in each IRIS. A value of 1 indicates an equal distribution of the six classes in the IRIS. The three other contextual variables characterize the built environment and were computed as the nearest distances of each house to (i) a primary/high school, (ii) a park and (iii) a shopping center. This information is available as shapefiles on the open data webpage of the Loire-Atlantique *département* (http://data.loire-atlantique.fr/donnees/).

In order to explore the possible impacts on the sale price of infrastructures known as alternatives to single-occupant car use, we first assessed the distance between each dwelling and such infrastructures, which vary depending on the sub-area studied. In the urban area (Nantes Métropole), distances to the nearest tram station, railway station and bike-sharing station were used. In the periurban and rural areas, having at least one "Lila" bus station in a buffer of 500 m radius near the home, one carpool area in a buffer of 1500 m radius, and the distance to the railway station were used. These thresholds were selected according to significance criteria derived from sensitivity analyses (from 250 m to 2000 m for "Lila" bus stations and from 500 m to 5000 m for carpool areas). Note that the "Lila" bus network is local public transport mainly dedicated to periurban and rural areas. All these public transport infrastructures were downloaded as shapefile points from the open data website of the city of Nantes (http://data.nantes.fr/donnees/). Euclidean distances between infrastructure points and dwelling points were then calculated. Table 1 presents these sustainable transport-based variables for each type of territory.

Once the database was built, multicollinearity between regressors was checked through the variance inflation factor (VIF). No values higher than 4 were present so all the variables were kept.

4.4. Descriptive Statistics

The overall descriptive statistics of the database are given in Table 1. The average sale price was €272,031 for the 1353 houses in the urban area and €188,566 for the 909 houses in the periurban and rural areas, while the average living surface area was quite similar in both spatial contexts (~104 m^2). In terms of environmental variables, the population density was approximately 3000 inhabitants/km^2 in the urban area and 196 inhabitants/km^2 elsewhere, while the unemployment rate was 9.9% and 7.8%, respectively. In the urban area, the average distance to the nearest tram/busway station was 2358 m, while it was 3788 m to the nearest railway station and 4363 m to the nearest bike-sharing station. In the periurban and rural areas, 34% of houses included a carpool area in a buffer of 1500 m and 45% a "Lila" bus station in a buffer of 500 m. Finally, the average distance to the nearest railway station was 12,580 m.

5. Model Calibration and Selection

The price of the house was retained as the dependent variable. After testing several modeling forms, a semi-logarithmic model was chosen. According to Martinez and Viegas [15], this specification usually produces robust estimates and enables convenient coefficient interpretation and is therefore widely used in the property value literature. Independent variables included house intrinsic characteristics, neighborhood variables and sustainable transport attributes.

First, the heteroskedasticity of the linear model (OLS) residuals was tested through a Breusch-Pagan test. As residuals were heteroskedastic (p-value < 0.001), Huber-White standard errors were used to ensure robust estimations. Then, the spatial dependence of the robust OLS residuals was tested through the global Moran test. Moran's I exhibited a significant p-value (<0.001), indicating a strong spatial autocorrelation. In order to overcome this, spatial models had to be used.

The spatial weight matrix for spatial models was based on the adaptive distance to a given number of k-nearest neighbor points, since our data are available as points (transaction postal addresses), which are irregularly scattered over the study area. These specificities make irrelevant the selection of weight matrices based on distance or contiguity. The weighting scheme was based on an exponential function, thus giving more weight to closer neighbors than farther ones. For each sub-area, the optimal k-nearest neighbors (from 2 to 50) were selected through an iterative process. The optimal number was that which minimized the AIC of the models. Twenty nearest neighbors were selected in the urban area and 8 in the periurban and rural areas.

One common concern relates to the selection of the most appropriate spatial model. There are several procedures suggested in the econometric literature (e.g., [40,41]. Florax et al. [40] proposed a bottom-up approach, consisting of running the OLS model first and then applying Lagrange Multiplier (LM) tests to test for lag and error spatial dependence. If both tests are significant, which was the case for our two samples (urban and periurban/rural areas), it is recommended to estimate the specification pointed to by the more significant of the two tests. Elhorst [41] also suggested starting with LM tests on the OLS model. If the OLS model is rejected in favor of the spatial lag (SAR), the spatial error model (SEM), or both, then the spatial Durbin model (SDM) should be estimated. A likelihood ratio (LR) test is subsequently used to examine whether the SDM can be simplified to the SAR or to the SEM.

The two procedures indicated that the SAR was the most appropriate model for the periurban/rural areas. Regarding the urban area, the first procedure pointed out the SAR, while the second one suggested the SDM. The SAR was selected rather than the SDM because of the lack of parsimony of the SDM (due to the numerous explanatory variables included in our models). Moran's I applied to the SAR models indicated no more autocorrelation issues, as reported in Table 2. The spatial parameters of the SAR models (ρ) were estimated by maximum likelihood, considered consistent for such a spatial model [42]. The other parameters were estimated by generalized least squares. Since the Breusch-Pagan test indicated significant heteroskedasticity on the SAR residuals, heteroskedasticity corrections were made to the SAR standard error estimates.

Table 2. Model diagnostics for Ordinary Least Squares (OLS), Spatial AutoRegressive model (SAR), Spatial Error Model (SEM) and Spatial Durbin Model (SDM) in the two areas.

Statistics	**Urban Area**				**Periurban/Rural Areas**			
	OLS	**SAR**	**SEM**	**SDM**	**OLS**	**SAR**	**SEM**	**SDM**
n	1353	1353	1353	1353	909	909	909	909
Moran's I	0.11 ***	−0.02	−0.00	−0.00	0.12 ***	0.02	−0.00	−0.00
ρ	n/a	0.42 ***	n/a	0.31 ***	n/a	0.19 ***	n/a	0.31 ***
λ	n/a	n/a	0.54 ***	n/a	n/a	n/a	0.54 ***	n/a
Robust LM_{lag}	n/a	67.1 ***	n/a	n/a	n/a	6.2 *	n/a	n/a
Robust LM_{err}	n/a	n/a	10.2 ***	n/a	n/a	n/a	4.5 *	n/a

* For $p < 0.05$; *** For $p < 0.001$. All models were corrected for heteroskedasticity.

In addition, Geographically Weighted Regression (GWR) models were run to explore the potential spatial heterogeneity of the price determinants. For the GWR models, an adaptive kernel bandwidth (i.e., a fixed number of neighbors) was chosen, since this is recommended when data points are sparsely distributed [43,44]. The same spatial weighting function as for spatial models was used (the exponential one). The optimal number of neighbors was also determined through an AIC minimization procedure and gave 64 for the urban area and 74 for the periurban and rural areas. To overcome issues related to edge effects inherent in any local analysis, all the data points (in the whole *département*) were fitted for each subsample and then data points outside the subsample studied were removed. In this way, even data points located at the boundary of the studied area were fitted with data points on all sides.

All analyses were performed with R ("spded" and "GWmodel" packages).

6. Results

6.1. Model Results for the Urban Area (Nantes Métropole)

Model diagnostics indicated GWR as the best model, followed by the spatial model and the OLS model, both in terms of AICc minimization and R^2/pseudo-R^2 maximization. The outputs of all the models (Akaike Information Criterion or AIC, adjusted R^2 for OLS and GWR models and Nagelkerke pseudo R^2 for spatial models) are given in Table 3.

Table 3. Results of estimations for the urban area (n = 1353).

Variable	OLS (*t*-Values)	SAR (*t*-Values)	GWR (Min)	GWR (Median)	GWR (Max)
(Intercept)	8.320 *** (19.98)	3.326 *** (5.46)	4.91	8.16	11.29
Intrinsic characteristics					
Log(Living surface area)	0.891 *** (28.28)	0.828 *** (29.08)	0.70	0.86	1.03
Log(Land surface area)	0.075 *** (6.38)	0.079 *** (9.91)	0.01	0.08	0.13
cod_constA	−0.185 *** (−4.00)	−0.172 *** (−4.55)	−0.41	−0.21	0.00
cod_constB	−0.227 *** (−7.75)	−0.220 *** (−7.72)	−0.34	−0.23	−0.12
cod_constC	−0.248 *** (−9.31)	−0.238 *** (−8.98)	−0.35	−0.24	−0.11
cod_constD	−0.183 *** (−7.42)	−0.176 *** (−7.72)	−0.36	−0.19	−0.11
cod_constE	−0.154 *** (−5.60)	−0.140 *** (−8.98)	−0.28	−0.14	−0.05
cod_constF	−0.012 (−0.39)	−0.009 (−7.09)	−0.12	−0.02	0.09
Neighborhood characteristics					
Log(DensPop)	0.040 ** (3.23)	0.024 * (2.22)	−0.02	0.04	0.13
Unemployment rate	−0.005 ° (−1.93)	−0.002 (−1.01)	−0.02	−0.01	0.01
Social diversity index	−0.469 (−1.40)	−0.082 (−0.26)	−1.69	−0.18	3.05
log(dist_school)	−0.030 ** (−2.86)	−0.033 *** (−3.22)	−0.07	−0.03	0.03
log(dist_park)	0.017 (1.45)	0.009 (0.78)	−0.05	0	0.10
log(dist_shop)	0.017 (1.37)	0.005 (0.49)	−0.04	0.01	0.08
Sustainable transport attributes					
log(dist_tram)	0.05 *** (4.58)	0.035 ** (3.23)	0.00	0.04	0.12
log(dist_railway station)	0.063 *** (5.46)	0.034 ** (3.05)	−0.04	0.07	0.19
log(dist_bike-sharing station)	−0.134 *** (−9.83)	−0.094 *** (−7.27)	−0.23	−0.15	−0.06
Rho		0.423 ***			
Model diagnostics					
AICc	375.284	264.620		251.526	
Nagelkerke R^2	-	0.592		-	
Adjusted R^2	0.551	-		0.617	
Moran's I (*p*-value)	0.001	0.961		0.080	

° For $p < 0.1$; * For $p < 0.05$; ** For $p < 0.01$; *** For $p < 0.001$.

In each model (OLS and SAR), the intrinsic characteristics of the houses sold in 2012, such as living surface area and land surface area, were positively associated with the dependent variable (Table 3). This means, for instance, that for the OLS model, if the living surface area increased by 1%, the price increased by 0.891%. The age of the houses (except for those built between 1991 and 2000) was negatively associated with the sale price compared to houses built after 2000.

Concerning the neighborhood characteristics, the population density exhibited a significant and positive association with the sale price in the two models (OLS and SAR), while the association with the distance to the nearest school was negative (if the distance to the nearest school increased by 1%, the price decreased by 0.03%). The other neighborhood variables were non-significant.

For sustainable transport attributes, the distance to the nearest tram station was positively associated with the sale price in the two models (OLS and SAR). It was the same result for train stations. For example, in the OLS model, increasing the distance by 1% was associated with an increase of 0.063% in the sale price. Finally, there was a negative relationship between the distance to "Bicloo" stations (bike-sharing stations) and the sale price in the two models (OLS and SAR). For example, in the OLS model, increasing the distance by 1% was associated with a decrease of 0.134%. Note that in all the previous and following models, the magnitude of such relationships is valid only for a marginal variation in the variable values, i.e., in the small vicinity of the observed transaction.

Regarding the GWR models, spatial nonstationarity was observed for the three transport-related variables (Table 3). The GWR slopes of the bike-sharing station variable (distance to the nearest station) were significantly negative everywhere (Figure 3a), ranging from −0.23 to −0.06, but exhibited spatial patterning in terms of intensity. For instance, the slopes were particularly strongly negative in the most western part of the area, meaning that the distance to the nearest bike-sharing station was strongly and negatively associated with the sale price. Railway station GWR slopes ranged from −0.04 to 0.19 and presented a cluster of high values just south of Nantes city, whereas patterns of non-significant coefficients appeared in many areas (Figure 3b). The GWR results for tram/busway station distances exhibited slopes ranging from 0.00 to 0.12 (Figure 3c). The western part of the area was characterized by significantly positive slopes, while they were mostly non-significant in the eastern part.

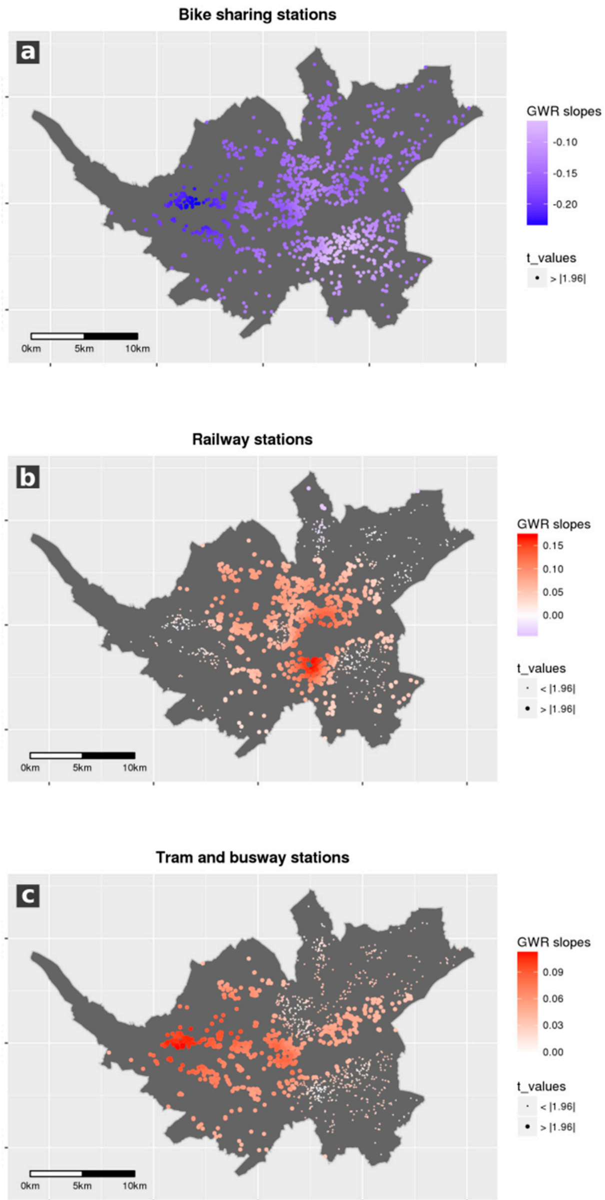

Figure 3. Map of GWR slopes in the Nantes Métropole area. (**a**) Bike-sharing stations; (**b**) Railway stations; (**c**) Tram and busway stations.

6.2. Model Results for the Periurban and Rural Areas

As for the urban area, GWR presented the best model diagnostics, followed by the spatial model (Table 4). The periurban models also outperformed the urban models (e.g., GWR adj. R^2 = 0.640 for the periurban area versus 0.617 for the urban area).

Table 4. Results of estimations for periurban and rural areas (n = 909).

Variable	OLS (*t*-Values)	SAR (*t*-Values)	GWR (Min)	GWR (Median)	GWR (Max)
(Intercept)	7.678 *** (15.47)	5.540 *** (8.94)	4.56	7.56	9.30
Intrinsic characteristics					
Log(Living surface area)	0.738 *** (16.84)	0.732 *** (16.62)	0.66	0.87	0.95
Log(Land surface area)	0.155 *** (7.83)	0.152 *** (12.47)	0.06	0.1	0.16
cod_constA	−0.403 *** (−8.89)	−0.402 *** (−11.00)	−0.48	−0.32	−0.16
cod_constB	−0.343 *** (−11.31)	−0.342 *** (−10.93)	−0.46	−0.27	−0.10
cod_constC	−0.256 *** (−6.53)	−0.255 *** (−6.99)	−0.41	−0.25	−0.16
cod_constD	−0.239 *** (−9.06)	−0.244 *** (−7.80)	−0.31	−0.19	−0.14
cod_constE	−0.145 *** (−4.57)	−0.145 *** (−3.60)	−0.20	−0.16	−0.08
cod_constF	−0.026 (−0.83)	−0.034 (−0.79)	−0.06	−0.02	0.02
Neighborhood characteristics					
Log(DensPop)	0.071 *** (4.09)	0.055 *** (3.33)	0.05	0.13	0.18
Unemployment rate	−0.027 *** (−4.71)	−0.018 ** (−2.92)	−0.02	0.00	0.00
Social diversity index	−0.766 ° (1.88)	0.542 (1.36)	−1.88	−0.19	3.52
log(dist_school)	0.003 (0.20)	−0.002 (−0.13)	−0.03	−0.00	0.02
log(dist_park)	−0.025 * (−2.32)	−0.025 * (−2.09)	−0.06	0.00	0.03
log(dist_shop)	−0.024 * (−2.42)	−0.21 * (−1.85)	−0.05	−0.02	0.03
Sustainable transport attributes					
Carpool area-1500_01	−0.087 *** (−3.93)	−0.064 ** (−2.59)	−0.22	−0.10	−0.04
nb_lila500_01	0.063 ** (2.77)	0.041 ° (1.75)	−0.02	0.02	0.06
log(dist_railway station)	−0.040 *** (−3.67)	−0.033 ** (−3.05)	−0.04	−0.01	0.04
Rho		0.193 ***			
Model diagnostics					
AICc	446.589	420.329		398.347	
Nagelkerke R^2	-	0.611		-	
Adjusted R^2	0.591	-		0.640	
Moran's I	0.001	0.144		0.147	

° For $p < 0.1$; * For $p < 0.05$; ** For $p < 0.01$; *** For $p < 0.001$.

Once again, in each model (OLS and SAR) there was a positive relationship between the intrinsic characteristics of the houses (living surface area and land surface area) and the sale price. Concerning the age of the houses, we found the same results in the periurban as in the urban area. Thus, except for houses built between 1991 and 2000, the construction period was negatively associated with the sale price compared to houses built after 2000.

For the neighborhood characteristics, there was a positive relationship between the population density and the sale price. Unemployment rate, distance to parks and to shopping centers exhibited negative slopes, while the other neighborhood variables were non-significant.

Concerning the sustainable transport attributes, the distance to the nearest railway station was negatively associated with the sale price in the two models (OLS and SAR), unlike the urban area. This relationship indicates an accessibility premium associated by house purchasers with railway stations. The relationship was similar regarding carpool areas, meaning that having one carpool area within 1500 m around the house was associated with a decrease in the sale price. However, having a "Lila" bus station within 500 m around the house was positively associated with the sale price only in the OLS model, and was non-significant in the SAR model.

The GWR results again revealed spatial nonstationarity in the periurban and rural areas (Table 4 and Figure 4). Slopes for the carpool area were significantly negative almost everywhere, with a cluster of low values in the middle northern part (Figure 4a). Regarding "Lila" bus stations, GWR slopes ranged from −0.02 to 0.06 and presented a more complex spatial patterning. Slopes were significant in the northern part of the periurban area, but mostly non-significant elsewhere, except in a few southern sectors (Figure 4b). Finally, the results for the distance to a railway station mainly revealed non-significant slopes, except in the middle and northwestern part with significant negative values (Figure 4c).

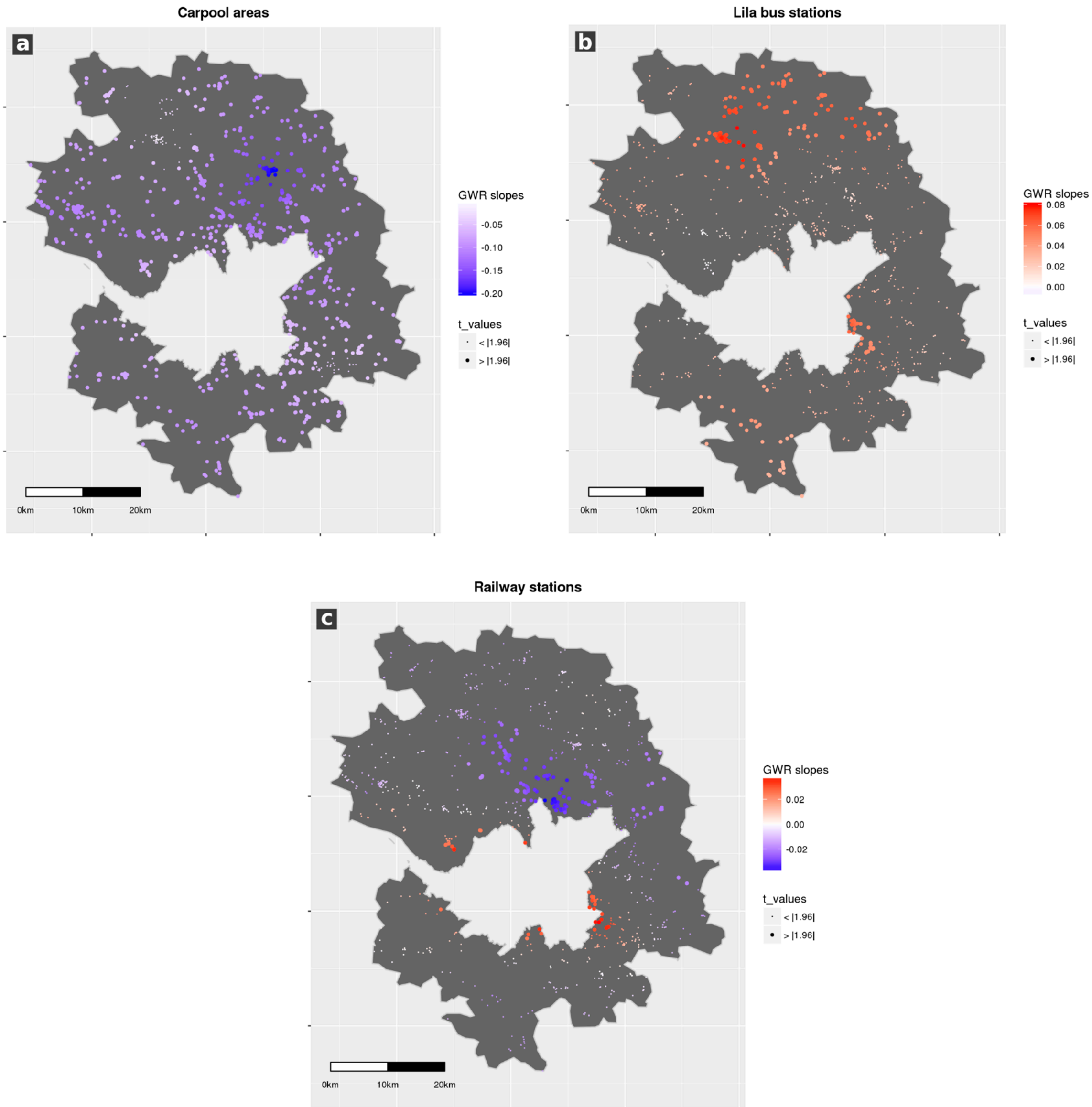

Figure 4. Map of GWR slopes in periurban and rural areas. (**a**) Carpool areas; (**b**) "Lila" bus stations; (**c**) Railway stations.

7. Discussion

In 2004, Time Magazine named Nantes "the most liveable city in Europe" and in 2013 it held the title of European Green Capital. Over the past 10 years, Nantes has been developing a sustainable transport policy with a focus on public transport and cycling [45]. In this study, we sought to explore whether the proximity to alternative offers to the private car affected house prices, not only in the urban area but also in periurban and rural areas.

Our results from the two samples (urban and periurban/rural areas) showed that the intrinsic characteristics of the house (living surface area and land surface area) were positively associated with the sale price. These results are consistent with other works (e.g., [46]). The population density also exhibited the expected relationships. Indeed, Saulnier [47] found the same results for the city of Grenoble.

7.1. Urban Area (Nantes Métropole)

In the urban area, three sustainable transport solutions were studied: tramways and the busway (BRT), railway stations and the bike-sharing system. We observed a positive association between the distance to the nearest tram station and the house prices in the two global models (OLS and SAR). According to Bowes and Ihlanfeldt [16], if station proximity has no effect or a negative effect on property values, the importance of the negative externalities emitted by the station are emphasized as an offsetting or dominant factor. Thus, it seems evident that the negative externalities of tramways and the busway (noise for example) have a negative impact on house prices [7,9,48]. However, the GWR model provided important information that questions this global result. Indeed, there were a few local differences in the impact of the tramway and busway infrastructure on the sale price (Figure 3c). We observed spatial nonstationarity for the tramway and busway variables. For example, the western part of the urban area was characterized by significantly positive slopes, while they were mostly non-significant in the eastern part. These results show that the tramway infrastructure did not have the same impact within the urban area. This can be seen as an indication to implement local transport policy. For example, the district of Bellevue in the western part of the urban area may need some additional funding to improve its image in the eyes of the potential house purchasers. In the framework of an enlarged urban renewal policy, this may yield even wider positive effects if wealthier households settle in the neighborhood.

The same positive relationship between the distance to nearest railway station and the sale price was observed in the global models (OLS and SAR). Once again, these results are consistent with other hedonic price studies, such as Bowes and Ihlanfeldt [16] and Seo et al. [22], which found that proximity to transportation infrastructure can reduce property values; this may be due to different nuisances (crime, noise and air pollution) associated with proximity to these facilities. However, this global result needs to be put into perspective because in the local model (GWR model), this relationship varied in the urban area. Indeed, the GWR slopes for the distance to the nearest railway station ranged from -0.04 to 0.19 (Table 3) and presented a cluster of high values just south of Nantes city, whereas patterns of non-significant coefficients appeared in many areas. The quality of the 2nd and 4th tramline/busway services (notably their frequency and time range) for the inhabitants of this area located close to the city center makes it superfluous to choose a house near a railway station, whereas the different types of nuisance remain [12].

Finally, the distance to the nearest "Bicloo" station (bike-sharing station) was negatively associated with house prices in the two models (OLS and SAR). In addition, the GWR model showed that this association exhibited spatial patterning in terms of intensity. Our results are consistent with El-Geneidy et al. [28] who found that the presence of a bike-sharing system is expected to increase property values. The authors concluded that policy makers could improve the local environment and benefit from economic gains in developing bike-sharing systems, as this transport policy could be in relation to higher property values, health benefits and greater welfare for residents.

7.2. Periurban and Rural Areas

In the periurban and rural areas, we focused on three sustainable transport systems: railway stations, carpool areas and "Lila" bus stations. The distance to the nearest railway station was negatively associated with house prices in the two global models. It is worth noting that this corresponds to a sign reversal compared to the urban area. This could be due to the fact that in urban areas, negative externalities associated with train stations (e.g., noise) outweigh the service provided, while in rural areas, having a train station not too far implies a significant gain in accessibility. In the periurban/rural areas, however, the matter is more complex than appears at first sight and was elucidated with the GWR model. In fact, the distance to the nearest railway station mainly revealed non-significant slopes, except in the middle and northeastern part with significant negative values (Figure 4c). In those areas, being located near a railway station of the Châteaubriant-Nantes line (North) or the Ancenis-Nantes line (East) significantly improves overall accessibility to Nantes; in the first case, because of the lack of alternative public transit offers in this relatively low-density periurban area and, in the second case, because of the intrinsic quality of the train line service, which provides daily commuters with a 16 min trip for a 43 km distance.

The availability of a carpool area in the house vicinity was significant in the two global models. Having at least one carpool area in a buffer of 1500 m around a house located in the periurban and rural areas was associated with a decrease of 8.7% (OLS) and 6.4% (SAR) in the sale price. Nevertheless, the GWR model exhibited slopes for carpool area ranging from -0.22 to -0.04 and was significant almost everywhere, with a cluster of low values in the middle northern part (Figure 4a). This result may be considered jointly with the proximity of the time-competitive Nantes-Ancenis (Northeast) railway line, which may be preferred to carpooling by daily commuters to Nantes city center. In the northern part, the "Lila" bus offer may be considered cheaper by poorer households than in the rest of the periurban and rural areas (unique ticket cost of €2 in 2012). Furthermore, the effective use of carpooling in 2012 was not as developed as it has since become, in particular for short and medium-distance trips, reinforcing the households' propensity to use alternative modes when they exist. The results are difficult to compare with other studies since, to our knowledge, there have been none on hedonic prices and carpool areas.

The "Lila" bus station, which was specified as at least one "Lila" bus station in a buffer of 500 m radius around the house located in the periurban and rural areas, exhibited a positive relationship with the sale price in the OLS model and became non-significant in the SAR model. The GWR model presented a more complex spatial patterning. Slopes were significant in the northern part of the area, but mostly non-significant elsewhere, except in a few southern sectors. This pattern is consistent with the absence of alternative modes in the northern area until 2014 and the Châteaubriant-Nantes railway line, with the exception of carpool areas that were potentially under-utilized in 2012. In the southeastern part of the periurban and rural areas, the "Lila" lines may be viewed as attractive by parents with children going to middle or high school within the urban area.

8. Conclusions

The objective of this paper was twofold: (i) to explore the relationships between several sustainable transportation infrastructures and the sale price of houses in urban and periurban/rural areas of Nantes and (ii) to derive from these analyses useful elements to help policy-makers reduce single-occupant car use. To achieve this, we used the hedonic price method and spatial econometric models (SAR and GWR).

The major finding of this study is that some sustainable transportation solutions had no or counterintuitive relationships with house prices but, above all, that these results exhibited spatial variations throughout the study area. We highlighted a territorial heterogeneity at two different scales. For example, in the urban area, the distance to the nearest tramway station was positively associated with house prices in the global model, but our GWR results showed that this association varied according to the place within the urban territory. The same rationale could be applied regarding the bike-sharing stations. This could serve as a useful indicator to implement local transport/mobility offers in sufficiently dense areas; in return, it could assist the design of urban planning policies to the extent that building housing near pre-existing mobility offers could prove profitable. In the same way, in the periurban and rural areas, the "Lila" bus station proximity was positively associated with the property sale price in the two global models but, once again, our GWR results showed a more complex spatial patterning. These results imply a spatial adaptation of transport policies and therefore different solutions to achieve sustainable mobility throughout the territories.

The main limitation of this study relates to the cross-sectional nature of the analyses, which does not allow for causal inference. Our results are also specific to this area and these data, so that any generalization of findings should be made with caution. In addition, some relevant variables possibly associated with house prices were missing (e.g., levels of criminality, noise and pollution), which could affect the estimated coefficients. Finally, although the results of the global models were robust and those of the GWR model (local model) were enlightening, these should be considered a first step in the analysis of sustainable mobility. They give indications about the various alternatives to single-occupant car use to be implemented in different types of territories. Nevertheless, other fine analyses are needed, such as qualitative studies, in order to implement a sustainable transport policy or sustainable urban development adapted to each neighborhood/territory.

Supplementary Materials: The following are available online at http://www.mdpi.com/xxx/s1, Table S1: Review of major recent studies assessing the relationships between various mobility services and housing price.

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Author Contributions: Julie Bulteau designed the study; Julie Bulteau and Thierry Feuillet performed the statistical analyses. Julie Bulteau, Thierry Feuillet and Rémy Le Boennec analyzed the results and wrote the paper.

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