TECHNICAL TRANSACTIONS 7/2018
ARCHITECTURE AND URBAN PLANNING
DOI: 10.4467/2353737XCT.18.097.8792
SUBMISSION OF THE FINAL VERSION: 28/06/2018

Ai Chen (ai.chen@upc.edu)
Carlos Marmolejo-Duarte (upc.carlos.marmolejo@gmail.com)
Centre for Land Policy and Valuations, Barcelona School of Architecture (ETSAB), Polytechnic University of Catalonia

Is the energy price premium spatially aggregated? A listing price analysis of the residential market in Barcelona

Czy ceny za energoszczędność są jednolicie rozłożone przestrzennie? Analiza cen rynku mieszkaniowego w Barcelonie

Abstract

Building energy efficiency has aroused much discussion around the world. Energy Performance Certificates (EPCs) and relevant regulations and legislation have been established and enforced in the past 15 years due to the extreme 40% consumption of total energy and 38% of total CO_2 emissions caused by residential buildings in Europe. This paper aims to confirm the energy premium in the Metropolitan Area of Barcelona (AMB) and the presence of spatial homogeneity of this energy premium with OLS hedonic prices and the GWR model. The results suggest that the energy premium causes a 12.2% housing price increase from Class G to Class A, or an implicit housing price rise of 1.9% with every ranking of EPC ordinal scale improvement. Furthermore, the areas with a higher incidence of energy labelling are situated in the middle and north-eastern parts of AMB that are inhabited by skilled professionals who more commonly have a higher university education.
Keywords: Energy Performance Certificates (EPCs), housing price, spatial aggregation

Streszczenie

Budowanie efektywności energetycznej wzbudzało liczne dyskusje na całym świecie. Świadectwa energetyczne (EPC) oraz odpowiednie przepisy i prawodawstwo zostały ustanowione i uchwalone w ciągu ostatnich 15 lat ze względu na ekstremalne 40% zużycie energii i 38% emisję CO_2 w europejskim sektorze budowlanym. Niniejszy artykuł ma na celu udowodnienie , że ceny za wprowadzanie rozwiązań energooszczędnych są wyższe w regionie metropolitalnym Barcelony (AMB). Przebadano równocześnie przestrzenną jednorodność energooszczędności, przy pomocy hedonistycznych cen OLS i modelu GWR. Wyniki sugerują, że wyższa cena za energoszczędność powoduje wzrost ceny mieszkań o 12,2% z klasy G do klasy A lub domniemany wzrost cen mieszkań o 1,9% przy każdej poprawce w rankingu na skali porządkowej EPC. Co więcej, obszary o wyższym wskaźniku etykiet energetycznych znajdują się w środkowej i północno-wschodniej części metropolii, gdzie przeważają mieszkańcy o wyższym wykształceniu uniwersyteckim oraz lepiej wykwalifikowani pracownicy.
Słowa kluczowe: Certyfikaty Efektywności Energetycznej (EPCs), ceny mieszkań, segregacja przestrzenna

1. Introduction

The concepts of "energy sustainability" and "environmentally friendly" arouse extensive attention and the discussion on how to utilize, save and regulate energy and reduce pollution has become a dominant issue. The building sector in Europe is responsible for 40% of total energy consumption and 38% of total CO2 emissions [1], thus causing justified economic, geopolitical and environmental concerns. For this reason, various countries and regions in Europe have begun to establish building energy management systems to monitor, supervise and improve energy efficiency; these include Energy Performance Certificates (EPCs), launched in 2003, the Building Research Establishment Environmental Assessment Method (BREEAM), which was launched in the UK in 1990, HQE in France, and Minergie in Switzerland.

Nowadays studies on energy efficiency and housing prices are focused on green investments [2–5], implicit energy prices on properties [6–8], and financial energy policies in the real estate market [9–14].

Numerous studies on the energy premium in the residential market have been conducted in recent years. The impact of different classes of EPC on selling prices varies from 0.4% in Oxford up to 11% in Vienna. However, the same impact of energy ranking contributes a 4% decrease and a 6% increase to property rents in the letting markets of Oxford and Vienna [15]. In general, energy performance certificates have a more significant impact on selling prices than rent and a larger impact in hinterlands (except Austria) than in capital cities. In the Turin residential market, there is a WTP selling premium of 26.44 euros/m2 [16] for each EPC ranking. A study of 300,000 homes in England [8] showed that the impact of EPCs was higher for terraced houses and apartments than detached houses. This means that potential consumption savings are more critical for cheaper housing, especially for buyers with lower income. Both the functional forms of the models used should be carefully studied due to the possible existence of energy submarkets and their socio-economic implications. In Spain the effect of EPC on residential prices has also been studied. Ayala et al [17] found an "opinion" market premium of 9.9% for houses certificated as highly energy efficient (A, B, C class) in the lower-level energy classes in 5 Spanish cities. Marmolejo [18] analysed listing prices in Metropolitan Barcelona and found an implicit price premium of 0.85% with a one-letter improvement in an EPC ordinal scale form (e.g. G = 1, A = 7) and a 9.62% property price increase for a Class A certificated dwellings in the Class G control group [18]. These authors employed urban attributes and achieved significant results that disclosed the spatiality of energy attributes.

However, not every energy certificate contributes to price premium. A study concerning Tokyo showed that the prices of the worst buildings in terms of energy efficiency are higher [19]. These authors argued these contradictory results are due to the fact that in some cases the Japanese green certificates (TGLSC) ignored the poor quality and location of buildings. Therefore, it is necessary to build more accurate and general econometric models from a locational perspective and control the quality of construction.

In summary, we found there are plentiful academic studies on residential energy market premium. However, housing energy efficiency submarkets (uneven spatiality) may have significant impacts on "Green Premium/Penalty", resulting in ineffective results and conclusions from a simple OLS analysis [8]. Thus, examination of this non-stationary impact across urban space is vital for identification of implicit energy housing prices and their aggregations, while avoiding energy poverty situations.

For this reason, this paper aims to 1) substantiate energy implicit housing prices in Metropolitan Barcelona and 2) examine the existence of spatial impacts of energy on housing prices. An Ordinary Least Squares Regression model (OLS) and Geographically Weighted Regression (GWR) is used to analyse implicit energy housing prices from the perspective of statistics and spatial distributions.

The rest of the paper is organized as follows: 1) first the methods, study area, data, and applied models are described; 2) second, the results of the aforementioned models are presented 3) finally, in the concluding section the findings and suggestions are discussed.

2. Methodology

This section describes the database and methods used. Along with the database from Habitaclia (one of the leading listing price websites in Barcelona) and socio-economic information from the Dwellings and Population Census across the Barcelona Metropolitan Area (AMB), the OLS hedonic prices model and the Geographically Weighted Regression (GWR) model are applied as follows.

2.1. Study area and data

Accessibility to city centres and sub-centres may have an impact on property prices; for this reason, the identification of functional limits and centralities is of paramount interest [20]. In this case, a functional delimitation of Barcelona Metropolitan Area (AMB) has been done by analysing the interaction values constructed from relevant commuting data. The result of such a method renders the image contained in Fig.1, which shows that AMB is made up of 184 municipalities, covers an area of 3,759 km2, and contains a population of 5.22 million.

Listing prices for apartments and flats from Habitaclia (April 2016) are the main resource of information, including residential addresses, architectural and structural building features, unit listing prices, etc. After excluding the outliers using the Mahalanobis distance method, which accounts for 10.86% of the original database (40,844 flats), there are 4,436 flats with effective information (including energy label). Furthermore, it is worth mentioning that more than half of them are certificated with an E class energy label, followed by 18.37% G class, 12.58% F class, and 10.66% D class. Since the majority of the flats (about 85%) in AMB were constructed before the year 2000, at which time building techniques were limited and construction codes were permissive, high-energy label classes (A, B and C class) account in total for less than 18.5% of properties. Simultaneously, relevant socio-economic information, population density, commuting time, and the environmental quality of neighbourhoods was collected from the Dwelling and Population Census INE 2001, Teleatlas (2010). On the other hand, accessibility and transport data was retrieved from the TeleAtlas cartography and the author's own vectorization of geographical attributes.

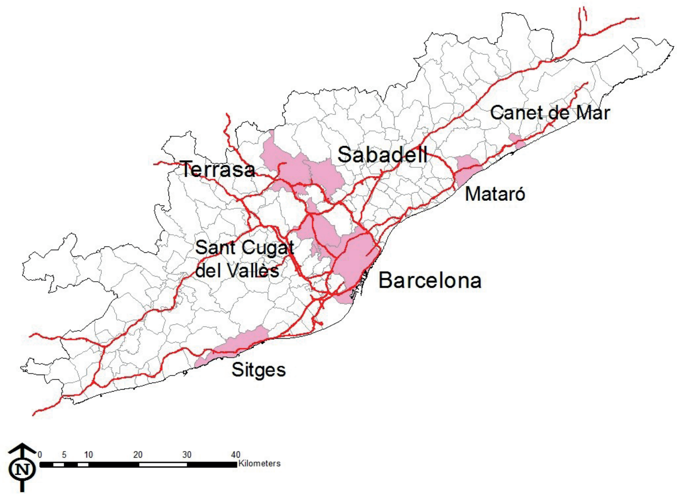

Fig. 1. Delimitation of Functional Barcelona Metropolitan Area
(own elaboration)

2.2. Methods

According to the general objectives, statistical description of the sample (Table 1) should be done by providing a comprehensive understanding and necessary information regarding the dependent variable (listing price of apartments) and independent variables (location and architectonic features of apartments). Subsequently, all attributes are employed and calculated by an OLS hedonic price model with the stepwise method, which can extract the significant attributes from this total sample. Thirdly, geographically weighted regression (GWR) will be executed with the same attributes to verify the spatial homogeneity of EPC class incidence over listing prices. Finally, a potential relationship between energy attributes and other socioeconomic attributes will be shown by graphic visualization, thus strengthening readers' comprehension.

OLS Hedonic Price Model

The model used in this paper is specified in the following equation:

$$Ln(P)i = B_i + \sum_{s=1}^{n} B_{is} SQ_{is} + \sum_{a=1}^{n} B_{ia} EL_{ia} + \sum_{n=1}^{n} B_{in} A_{in} + \sum_{e=1}^{n} B_{ie} NE_{ie} + \varepsilon_i \qquad \text{(I)}$$

In equation (I), the logarithm of the listing price P of apartment *i* depends on a set of variables related to structural and qualitative dimension (*SQ*), energy label dimension (*EL*) referring to EPC class, accessibility dimension (*A*) as well as neighbouring and environmental dimensions (NE).

Table 1. Descriptive Statistics of the depurated sample

Dimensions	Variables	N	Minimum	Maximum	Mean	Std. Deviation
Structural and Qualitative Dimension (SQ)	Unit Price (euro/sq.m)	4,436	902	3,992	2,188	793
	Gross price (euro)	4,436	41,800	1,200,000	194,350	117,898
	Gross Area (m2)	4,436	20.00	313.00	87.01	31.75
	Areas^2 (m4)	4,436	400.00	97,969	8,579	7,707
	Number of Bedrooms	4,436	1	8	3.07	4.00
	Number of Bathrooms	4,436	0	4	1.35	0.53
	Levels	4,436	0	14	2.09	1.98
	Construction Year	4,436	1817	2016	1968	28
	Terrace Areas (m2)	4,436	0	180	8.32	16.79
	Dummy Storage	4,436	0	1	0.20	0.40
	Dummy Laundry	4,436	0	1	0.50	0.50
	Dummy Air Conditioner	4,436	0	1	0.44	0.50
	Dummy Heating	4,436	0	1	0.67	0.47
	Dummy High Quality Properties	4,436	0	1	0.03	0.18
	Dummy Elevator	4,436	0	1	0.68	0.47
	Dummy Swimming Pool	4,436	0	1	0.10	0.30
Accessible Dimension (A)	Dummy Access to Highway	4,436	0	1	0.88	0.32
	Dummy Access to Rail Station	4,436	0	1	0.51	0.50
	Distance to CBD (km)	4,436	0.12	62.01	17.28	14.39
	Working Commuting (minutes)	4,436	11.54	41.44	24.22	4.36
	Distance to Rail Station (km)	4,436	0	10.14	0.83	1.07
	Distance to Highway (km)	4,436	0.01	11.26	1.91	1.52
Neighbouring and Environmental Dimension (NE)	Percentage of People without Studies (%)	4,436	3.78	45.68	14.67	5.73
	Percentage of People with Primary Studies (%)	4,436	8.31	50.74	24.90	5.68
	Percentage of People with Secondary Studies (%)	4,436	20.77	67.1	46.84	5.26
	Percentage of People with University Studies (%)	4,436	0.63	50.55	13.59	8.96
	CP High Income	4,436	-2.39	2.61	0.14	0.92
	CP Medium Income	4,436	-1.26	2.09	0.44	0.51
	CP Medium-Low Income	4,436	-2.67	3.36	-0.09	0.85
	Proportion of Ruined Buildings (%)	4,436	0	59.38	1.27	2.76
	Proportion of Bad functional Buildings (%)	4,436	0	40.87	2.73	5.49
	Proportion of Deficient Buildings (%)	4,436	0	73.91	9.73	10.85
	Proportion of Good Buildings (%)	4,436	0	100	86.27	14.76
	Proportion of Noise Annoyance opinion (%)	4,436	5.15	77.43	38.12	11.40
	Proportion of Pollution opinion (%)	4,436	1.72	82.14	22.05	11.82
	Proportion of Dirty Streets opinion (%)	4,436	0.75	84.97	36.47	12.69
	Proportion of Bad Transportation opinion (%)	4,436	0.26	81.07	13.41	12.72
	Proportion of Deficient Green Zone opinion (%)	4,436	1.12	90	35.68	16.82
	Proportion of Delinquency opinion (%)	4,436	3.04	90.91	27.23	16.27
	Dummy Access to Sea (in 200 meter)	4,436	0	1	0.04	0.19
Energy Label Dimension (EL)	EPC_A	4,436	0	1	0.03	0.18
	EPC_B	4,436	0	1	0.01	0.10
	EPC_C	4,436	0	1	0.04	0.18
	EPC_D	4,436	0	1	0.11	0.31
	EPC_E	4,436	0	1	0.50	0.50
	EPC_F	4,436	0	1	0.13	0.33
	EPC_G	4,436	0	1	0.18	0.39
	Ord_EPC (from A=7 to G=1)	4,436	1	7	2.85	1.32

Source: own elaboration

In the SQ dimension, there are several direct and indirect attributes, including price per square metre, total price of flat, gross area, number of bedrooms/bathrooms as well as the level on which the apartment is located, building construction year, terrace area, and storage and laundry facilities (Yes = 1, No = 0). It is noted that two variables, square area and area/rooms, are specified, which reduces the extreme data bias of luxury flats. Also, this dimension includes the presence of air-conditioning, heating, and the overall quality of finishings. Other attributes refer to the presence of a lift or common swimming pool in the building where the apartment is located. It can be seen that the average size of flats is 87 square metres, the average listing price is 2,188 euros per square metre, and the average apartment consist of 3 bedrooms and 1.5 bathrooms. More than half have laundry rooms, heating appliances and lift.

In dimension A, the accessibility to transport infrastructure (highway, railway, subway) or the city centre, as well as commuting time to work, is included. Note that data concerning public transport can be easily acquired by Nearest Neighbour Analysis (NNA) in ArcGIS. Hence, it is also useful to introduce these dummy variables about accessibility to public transport that result from buffer zones with a radius of 400 metres and 800 metres respectively in urban and suburban areas. In such cases, over 50 per cent of properties are located 17 km, 0.83 km and 1.91 km distance to CBD, train station and highway, respectively. In addition, the average commuting time from house to workplace is 24 minutes according to the Census. Less commuting time possibly means more time spent on entertainment activities and lower transport costs, which promotes a willingness to purchase and thus higher housing prices.

The NE dimension consists of each neighbourhood's education and income level as well as building condition and perception of the built environment (all this data comes from the Census). In this sample, almost 50% of the people have some secondary education, followed by primary education (24.9%), no education (14.67%) and university education (13.59%). Similarly, this corresponds to the distribution of income levels, for which family groups with a medium income is predominant. It is easy to see that neighbourhoods with better educated households are commonly more affluent than those with less educated residents. Education levels and income levels show a higher correlation coefficient, probably resulting in multi-collinearity. Furthermore, in the opinion of households, over 86% of buildings are considered functionally perfect, and around 33% of them suffered from noise annoyances, dirty streets, or deficient green zones. Waterfront views can also be represented as location and neighbourhood qualities that affect buying preferences and decision-making. Just a few properties are located within 200 metres of the sea; therefore, even in a coastal city such as Barcelona, properties with a perfect sea view are scarce.

The EL dimension shows 2 different energy ranking scales: I) Ordinal energy rankings from Class A to Class G are assigned from 7 to 1; II) Nominal energy rankings, in fact, are energy ranking dummy variables (e.g. if a property is certificated with Class E, just EPC_E dummy will be numbered "1", the other 6 Classes are "0")

Geographically Weighted Regression Linear Model

In order to examine whether and how energy attributes spatially impact housing prices, Geographically Weighted Regression (GWR), a prevalent spatial analysis model, has been employed. It could resolve autocorrelation issues and represent a "soft window" approach to submarket identification (non-stationary influence) [21].

$$Ln(P)i = B_i(u_i,v_i) + \sum_{s=1}^{n} B_i(u_i,v_i)SQ_{is} + \sum_{a=1}^{n} B_{ia}(u_i,v_i)EL_{ia} + \qquad \text{(II)}$$

$$+\sum_{n=1}^{n} B_{in}(u_i,v_i)A_{in} + \sum_{e=1}^{n} B_{ie}(u_i,v_i)NE_{ie} + \varepsilon_i$$

Where (u_i, v_i) denotes the coordinates of the *i*th point in space and $\beta_k(u_i, v_i)$ is a realization of the continuous function $\beta_k(u,v)$ at point i. That is, a continuous surface of parameter values is allowed, and measurements of this surface are taken at certain points to denote the spatial variability of the surface. Regarding the primary OLS hedonic price model, it is easy to find the spatial information of every observation calculated in the GWR model that can reveal a spatial relationship among various attributes from diverse dimensions. Also, with a spatial distribution of energy attributes (Energy label) and their significances, it is easy to estimate the existence of non-stationary energy impacts on urban space.

3. Results

In this section, we aim to explore how the energy category premium affects housing prices and then clarify its spatial distribution, which is supposed to be a discontinuous diversification. Table 2 presents estimation results from the OLS hedonic prices model and is classified by hierarchical regression into four dimensions. That is, attributes from the structural and qualitative dimension, accessible dimension, neighbouring and environmental dimension as well as energy label dimension are calculated in sequence. It shows a 1.9% increase in housing prices while promoting a one-level energy label or an increase 12.2% of property prices along with the nominal energy ranking improved from Class G to Class A. Subsequently, Table 3 shows estimation results from the GWR model and reveals a remarkable spatial variability for the core "Energy label" variable. Finally, spatial aggregations of energy labels are illustrated graphically, and their relationships with other socioeconomic attributes are elaborated below.

3.1. Energy implicit housing prices

Hierarchical regression is the prevalent analysis method to explore whether additional attributes contribute to improving the model and core variables are generally applied in the final model. Columns 1–3 of Table 2 show OLS estimation results by structural, qualitative, accessible and environmental dimensions progressively. Columns 4 and 5 show relevant energy label variables in ordinal and nominal forms, in addition to the attributes introduced above.

In general, a significant growth of R square adjusted from 0.577 to 0.775 represents a better linear fitting goodness. That is to say, MOD4 and MOD5 (including four-dimensional attributes) in Table 1 can explain 77.5% of the variance of these apartments' listing selling prices based on a 95% confidence interval, compared with other models. The attributes from the structural and qualitative dimensions are still the dominant factors that affect housing prices, followed by the Neighbourhood and Environment dimensions, and the Accessibility dimension across Metropolitan Barcelona.

With crosswise comparison, all estimation coefficients changed slightly regarding MOD3, which is a completed variable set that excludes the energy efficiency label. Coefficients of variables in the SQ dimension decrease while those of the variables in the other 2 dimensions increase when the energy efficiency label is introduced. The most changed variables relate to the presence of an elevator and the number of bathrooms, decreasing 0.6% and 0.5% respectively; the variables relating to the presence of a high-quality kitchen, air conditioner, heating and high-quality properties decreased only a little, by an average of 0.3%. This means that the possible impact of an elevator on housing prices after taking into consideration energy label information decreases by 0.6%, controlled other variables. In the same way, the possibility of impacts on housing prices drops 0.5% and 0.3% regarding the previous variables stated. On the other hand, the possible impacts of "access to highway " and "access to sea" on housing prices increase 0.4% and 0.5% respectively, where otherwise almost remain the same. Energy label class does indeed have an impact on property price.

According to the standardized coefficient beta, the most critical attribute on housing prices in the SQ dimension is gross area while the square of gross area has a negative sign, which represents the presence of the decreasing marginal utility principia. Subsequently, the presence of an elevator and public swimming pool lead to a significant increase of 11.3% and 11.9% in listing prices, respectively. Likewise, there are respective increases of 5.9% and 8% in residential value for apartments equipped with air conditioning and heating. The results demonstrate that necessary facilities and appliances in flats and buildings are mostly responsible for gross property prices in this physical characteristics dimension. Note that the variable of a terrace area impacts housing prices with a 0.2% increase that remains the same whatever the energy label.

In the accessibility dimension, access to highway and transport stations bring about increases of 3.8% and 4.2% respectively for residential prices. In other words, if an apartment is located in a municipality with a highway ramp or within 400 m. or 800 m. of a train station (urban/suburban location), then there is an average 4% rise in property prices. In terms of distance to CBD, its coefficient demonstrates that the price of flats located far away from CBD decrease by 0.8% for each kilometre.

In the neighbourhood and Environment dimension, the within 200 metres of the sea variable, the proxy of landscape environment, shows the most significant influences. Flats near the sea have a 12.9% higher price, which implies a strong willingness to pay for this feature. On the contrary, noise pollution seems to have no obvious effects on housing prices. It can be deduced that benefits from the conglomeration of commercial and entertainment activities as well as the availability of transport can offset, to some extent, the influence of noise annoyance. In other words, buyers are willing to suffer noise annoyance to a certain degree in order to enjoy conveniences of daily life. The proportion of the population with a university degree represents potential consumers' social class and wealth level; this adds 1.8% to property prices for each percent that each proportion increases.

In Column 4, energy label is statistically significant in the model. According to the coefficients, when other variables are controlled for, the apartments' price increases 1.9% with each better energy class. The coefficients for the control variables are generally consistent with expectations. More details on green premiums are listed in Column 5, where six energy label dummy variables (from A to F) replace the previous ordinal energy label, and the reference group is Class G. Class A, C, D, E are significantly positive while Class B and Class F are insignificant. In general, the green premium increases along with energy rating improvement:

in comparison to "Class G", flats certificated as Class A show the highest increase of 12.2%, followed by 8% for Class C, 8.1% for Class D and 2.2% for Class E. In line with expectations, differences of energy label ranking (from efficiency to inefficiency) contribute to a continuous increase of property price.

Table 2. Estimation of OLS Model

	MOD1	MOD2	MOD3	MOD4	MOD5
R2	0.578	0.694	0.773	0.775	0.776
R2 adjusted	0.577	0.693	0.773	0.775	0.775
(Constant)	10.612	10.674	10.432	10.4	10.42
	(0.032***)	(0.032***)	(0.031***)	(0.031***)	(0.031***)
Gross Areas (m2)	0.015	0.015	0.014	0.014	0.014
	(0.001***)	(0.001***)	(0.000***)	(0.000***)	(0.000***)
Areas^2 (m4)	-2.12E-05	-2.58E-05	-2.90E-05	-2.84E-05	-2.88E-05
	(0.000***)	(0.000***)	(0.000***)	(0.000***)	(0.000***)
Number of Bathrooms	0.082	0.112	0.099	0.094	0.093
	(0.012***)	(0.011***)	(0.009***)	(0.009***)	(0.009***)
Terrace Areas (m2)	0.0001	0.001	0.002	0.002	0.002
	(0.000)	(0.000***)	(0.000***)	(0.000***)	(0.000***)
Dummy Quality Kitchen	0.057	0.04	0.054	0.052	0.052
	(0.011***)	(0.009***)	(0.008***)	(0.008***)	(0.008***)
Dummy Air Conditioner	0.092	0.046	0.065	0.061	0.059
	(0.011***)	(0.010***)	(0.008***)	(0.008***)	(0.008***)
Dummy Heating	0.065	0.108	0.083	0.08	0.08
	(0.012***)	(0.011***)	(0.009***)	(0.009***)	(0.009***)
Dummy High Quality Properties	0.1	0.058	0.06	0.057	0.056
	(0.029***)	(0.025*)	(0.022**)	(0.022**)	(0.022**)
Dummy Swimming Pool	0.074	0.178	0.12	0.119	0.119
	(0.017***)	(0.000***)	(0.013***)	(0.013***)	(0.013***)
Dummy Elevator	0.167	0.143	0.119	0.113	0.113
	(0.011***)	(0.000***)	(0.008***)	(0.008***)	(0.008***)
Dummy Access to Highway		0.059	0.034	0.038	0.038
		(0.014***)	(0.012**)	(0.012**)	(0.012**)
Dummy Access to Rail station		0.089	0.042	0.042	0.042
		(0.009***)	(0.008***)	(0.008***)	(0.008***)
Distance Access to CBD		-0.011	-0.008	-0.008	-0.008
		(0.000***)	(0.000***)	(0.000***)	(0.000***)
Dummy Access to Sea			0.125	0.13	0.129
			(0.020***)	(0.020***)	(0.020***)
Proportion of Noise Annoyance opinion (%)			0.003	0.003	0.003
			(0.000***)	(0.000***)	(0.000***)
Percentage of People with University Studies (%)			0.017	0.018	0.018
			(0.000***)	(0.000***)	(0.000***)
Ord_EPC				0.019	
				(0.003***)	
EPC_A					0.122
					(0.022***)
EPC_B					0.021
					(0.037)
EPC_C					0.08
					(0.022***)
EPC_D					0.081
					(0.015***)
EPC_E					0.022
					(0.010*)
EPC_F					0.024
					(0.014)

Notes: *Significant at 1%; **Significant at 0.5%; *** Significant at 0.1%; n/s not significant; Dependent variable: Ln gross price

Source: own elaboration

3.2. Energy Spatial Impacts on Housing Prices

Simple OLS analysis may cause incorrect understanding and misjudgement if the distribution of attributes across the urban space shows an uneven spatial layout [8]. In order to solve this problem, in the following section I will apply the Monte Carlos Significance Test [22], and a Geographically Weighted Regression model that produces spatial coefficients for each observation.

Table 3. Estimation of GWR Model

GWR Model		Akaike information criterion	
R2	0.813	OLS	188.33
R2 adjusted	0.808	GWR	-403.14
Sigma (SE)	0.2279		

B Distribution Statistic				***Significance Test***	
	Lower quartile	***Huber's M-estimator***	***Upper quartile***	***Monte Carlo test for spatial variability (p-value)***	
(Constant)	10.4263	10.5937	10.6387	0.0000	***
Gross Areas (m^2)	0.0137	0.0150	0.0164	0.0000	***
Areas^2 (m^4)	0.0000	0.0000	0.0000	0.0900	n/s
Number of Bathrooms	0.5360	0.0899	0.1149	0.0000	***
Dummy Swimming Pool	0.1178	0.1427	0.1762	0.0000	***
Terrace Areas	0.0018	0.0020	0.0022	0.5500	n/s
Dummy Elevator	0.1041	0.1291	0.1362	0.0100	**
Dummy Quality Kitchen	0.0435	0.0548	0.1362	0.4800	n/s
Dummy Air Conditioner	0.0492	0.0580	0.0631	0.7100	n/s
Dummy Heating	0.0817	0.0918	0.0968	0.0500	*
Dummy High Quality Properties	0.0509	0.0633	0.0906	0.8600	n/s
EPC_A	0.0777	0.1543	0.1852	0.1200	n/s
EPC_B	-0.0018	0.0395	0.0842	0.5300	n/s
EPC_C	0.0485	0.0961	0.1383	0.0000	***
EPC_D	0.0535	0.0717	0.0981	0.0000	***
EPC_E	0.0219	0.0243	0.0266	0.6200	n/s
EPC_F	0.0223	0.0410	0.0523	0.3100	n/s
Dummy Access to Highway	-0.0608	0.0238	0.0863	0.0000	***
Dummy Access to Railway	0.0101	0.0168	0.0863	0.2400	n/s
Distance to CBD	-0.0333	-0.0171	-0.0073	0.0000	***
Dummy Access to Sea	0.1201	0.1684	0.2569	0.0000	***
Proportion of Noise Annoyance opinion	0.0009	0.0019	0.0027	0.0000	***
Percentage of People with University Studies	0.0122	0.0138	0.0163	0.0000	***

ANOVA	***Sum of squares***	***Df***	***Mean square***		
OLS residuals	268.1	23		N nearest neighbors	2256
GWR improvement	43.6	95.25	0.4582	Num. locations to fit	4436
GWR residuals	224.4	4317.75	0.052		
	F	Sig			
	8.8164	0.0000			

Notes: *Significant at 1%; **Significant at 0.5%; *** Significant at 0.1%; n/s not significant; Dependent variable: Ln gross price; GWR Adaptive kernel crossvalidated.

Source: own elaboration

Table 3 contains the results from the GWR model; as can be seen, there are 2,256 cross-validated cases (numbers locations to fit is 4,436 cases) used by the adaptive kernel and adjusted R2 increases from 0.775 to 0.808. This means the GWR model can explain 80.8% of cases, namely the local regression model can give a more accurate result than the OLS model. Regarding the Akaike information criteria, it shows a dramatic decrease from 256.06 to -371.59. Meanwhile, relative sigma decreases slightly, which suggests that GWR can give a more accurate result than the OLS model. In the table, upper and lower quartiles, as well as Huber's M-estimator, which is more robust than the mean, are detailed.

Compared with the coefficient of OLS, coefficients of built areas and the proportion of high education, as well as the proportion of noise annoyance remain almost steady, while most variables present a slightly increasing impact, such as within 200 m. of the coast, the presence of a swimming pool and elevator. There are two significant energy-efficient attributes (Class C and Class D) in the Monte Carlo test, in which these two attributes show the expected uneven spatial impacts on housing prices. Separately, the coefficient of Class C increases slightly to 9.6%, but D decreases to 7.71% in listed property prices compared to the reference group (Class G), which corresponds more to the expectations than the previous results from the OLS model (8% and 8.1% respectively).

This spatial variation in the remaining variables is not significant due to a reasonably high probability that the variation occurred by chance. This is useful information because now, in terms of mapping the local estimates, these variables exhibit significant spatial non-stationarity. These results suggest a non-stationary impact of energy label.

3.3. Spatial aggregation

Before showing a series of visualizations of spatial energy data with socio-economic variables, a Pearson correlation is produced to detect the inner relationship between Class C and Class D and other variables. These two energy labels have a more significant impact on areas where low-income citizens live (more blue-collar workers with lower price per square metre dwellings). In other words, they have a negative impact on areas inhabited by residents with higher income or elite professions. This means that energy penalties from a lower EPC rating in deprived areas are more prominent, which proves that EPCs do not affect the real estate market equally across urban areas, resulting in building energy-efficient segmentation. What is more, the more significant the differentiation of energy-efficient segmentation, the more likely it is that contradictions of social-class and energy dilemmas are produced.

As shown in Fig. 2–1 and 2–2, spatial energy distributions (Class C and Class D) influence housing prices for all observations. As stated above, Class C and Class D passed the Monte Carlo Test, demonstrating in this general sample that impacts from these two levels on housing prices are unsteady and cause a submarket of energy-efficient flats. From the left two figures, it is easy to see that energy labels Class C and D present a conglomeration in similar districts and zones: i) the middle part of AMB shows housing price sensitivity to energy label impacts, especially in Mollet del Vallés and Granollers for Class C and Terrassa for Class D; ii) observations with inert or even negative impacts of energy label on housing prices located in

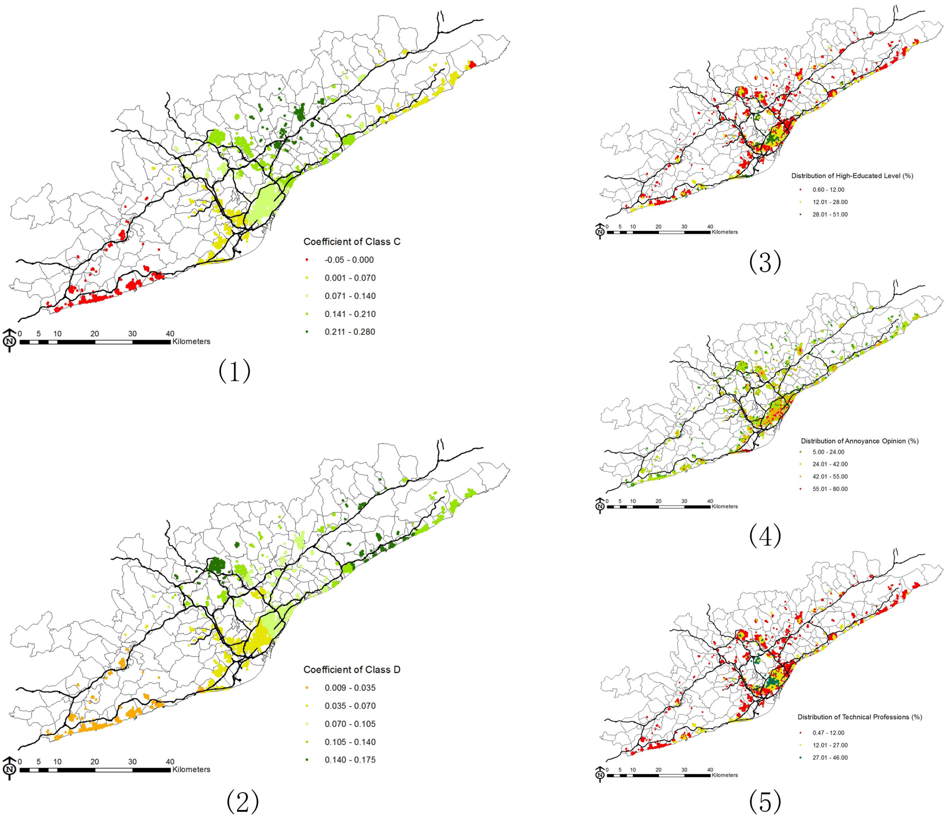

Fig. 2. Spatial Distribution of Energy Label and Other Variables. 2–1: Class C; 2–2: Class D; 2–3: proportion of university studies; 2–4: proportion of noise annoyance; 2–5: proportion of technical professions (own elaboration)

the south-western part of AMB; iii) for north-eastern AMB, its sensitivity to energy labels is inversely related to Class C and Class D, where a negative impact for Class C and a significant influence for Class D are shown.

In order to explore the intrinsic relationship between the distribution of energy efficiency impacts and other corresponding social or architectural features, a visualization of the relevant spatial distribution of following attributes will be produced that will reveal some evidence about the inner association.

As for the social-class attributes, the neighbourhoods with a higher proportion of university-educated households (similarity to the variable – PC households income) are mostly located around the centre of Barcelona city (San Cugat del Vallés and Sabadell) where energy label impacts on residential value are also significant (Fig. 2–3). This is due to their extraordinary economic and employment circumstances, which attract more residents with a high-level education. The more that highly educated, high-income families move in, the more chance there is that they can accept and afford premium property prices. This is also similar to the "Technical professions" attribute (Fig. 2–5). However, it is clear that the conglomeration of energy label effects on housing prices is more distinct and their borders transition more smoothly, compared with the distribution of university-educated groups and technical professionals in these districts and sectors. It is supposed that more factors contribute to the effects of energy label in addition to the socio-economic attributes above. It is worth noting that in the centre of Barcelona city, where citizens suffer from massive noise pollution (Fig. 2–4), the energy premium is higher than in the surrounding areas. Prompt installation of double-glazed windows probably increases the level of energy labels in which facilities materials are of importance to estimate its energy performance ranking [23, 24], in order to enjoy life conveniences (e.g. commercial activities, transport, etc.). In other words, there is a higher demand for energy efficiency measurements in noise-contaminated areas, further illustrating the greater sensitivity to high-level energy labels.

In general, the energy-label attribute does, to some extent, have a non-stationary impact of energy premium across urban areas; furthermore, there are certain inner and implicit relationships between energy label and socio-economic attributes. Therefore, which attributes play a decisive role in the spatial aggregation of energy implicit housing prices and how to judge and quantify them is a task for future research.

4. Conclusions

Plenty of studies based on the Hedonic Pricing method and model have confirmed that energy labels have an impact on housing prices. However, the effectiveness of this mandatory certificates program is still unknown due to the different variables chosen and real estate market conditions [15, 16]. As the second largest metropolitan area in Spain, Metropolitan Barcelona has achieved a great deal in terms of building energy efficiency, and its dynamic real estate market offers enough information to survey how the EPC program is progressing. Little research has discussed the socio-economic impact of energy efficiency on property prices in Spanish urban areas, despite a 9.9% increase of housing prices for dwellings certificated with high energy ranking in 5 Spanish cities [17] and a 9.62% increase of listing prices of properties improved from Class G to Class A in Barcelona [18].

In general, the Results from this OLS hedonic price model suggest that mainly structural and quality features play a significant role in housing prices, followed by accessibility, neighbourhood and environment. After all, the majority of the aforementioned attributes relate to the physical features of houses, their location, and their energy efficiency. In Metropolitan Barcelona the certificated energy label A of renovated flats can charge, related to flats with label G, for a 12.2% increase premium or an increasing effect, 1.19% of listing prices, of a one-letter improvement in energy efficiency. This is a higher premium price than that stated in previous studies in Spain (9.62%/0.85%) and we inferred that the number of green properties and the capitalization of energy efficiency, along with the mandatory EPC program progressed and perception of energy label information enhanced, are gradually increasing and strengthening.

The results of the Geographically Weighted Regression (GWR) model and Monte Carlo Significance Test indicate that, as expected, energy label Class C and D, in addition to other socioeconomic attributes, show an uneven distribution across urban space. The centre of AMB shows the highest effect of energy label on housing prices, followed by the north-eastern and south-western parts. This corresponds to the distribution of high-level professions (managers, technicians, etc.) and neighbourhoods with highly educated citizens, demonstrating that such socio-economic attributes do matter in the uneven effect of energy label class on property prices. Furthermore, research on the inner social meanings and relations behind energy labels should be conducted in the future to promote the EPC program and relevant energy policies.

This paper is derived from first author's MsC Thesis, as part of the EnerValor project MINECO/FEDER 2015-63606R.

References

[1] Arcipowska A., Anagnostopoulos F., Mariottini F., Kunkel S., *Energy performance certificates across the EU–a mapping of national approaches,* The buildings Performance Institute Europe (BPIE), Brussels 2014.

[2] Heinkel R., Kraus A., Zechner J., *The effect of green investment on corporate behavior,* "Journal of Financial and Quantitative Analysis", Vol. 36/2001, Issue 4, 431–449.

[3] Orsato R.J., *Competitive environmental strategies: when does it pay to be green?,* "California Management Review", Vol. 48/2006, Issue 2, 127–143.

[4] Chen Y.S., *The drivers of green brand equity: Green brand image, green satisfaction, and green trust,* "Journal of Business Ethics", Vol. 93/2010, Issue 2, 307–319.

[5] Thatcher A., Milner K., *Is a green building really better for building occupants? A longitudinal evaluation,* "Building and Environment", Vol. 108/2016, 194–206.

[6] Miller N., Spivey J., Florance A., *Does green pay off?* "Journal of Real Estate Portfolio Management", Vol. 14/2008, Issue 4, 385–400.

[7] Eichholtz P., Kok N., Quigley J. M., *Doing well by doing good? Green office buildings,* "The American Economic Review", Vol. 100/2010, Issue 5, 2492–2509.

[8] Fuerst F., McAllister P., Nanda A., Wyatt P., *Does energy efficiency matter to home–buyers? An investigation of EPC ratings and transaction prices in England,* "Energy Economics", Vol. 48/2015, 145–156.

[9] Jaffe A.B., Stavins R.N., *The energy–efficiency gap What does it mean?,* "Energy Policy", Vol. 22/1994, Issue 10, 804–810.

[10] Oikonomou V., Becchis F., Steg L., Russolillo D., *Energy saving and energy efficiency concepts for policy making,* "Energy Policy", Vol. 37/2009, Issue 11, 4787–4796.

[11] Allcott H., Mullainathan S., *Behavior and energy policy,* "Science", Vol. 327/2010, Issue 5970, 1204–1205.

[12] Gillingham K., Newell R.G., Palmer K., *Energy efficiency economics and policy,* "The Annual Review of Resource Economics", Vol. 1/2009, Issue 1, 597–620.

[13] Gillingham K., Palmer K., *Bridging the energy efficiency gap: Policy insights from economic theory and empirical evidence*, "Review of Environmental Economics and Policy", Vol. 8/2014, Issue 1, 18–38.
[14] Gillingham K., Rapson D., Wagner G., *The rebound effect and energy efficiency policy*, "Review of Environmental Economics and Policy", Vol. 10/2016, Issue 1, 68–88.
[15] Mudgal S., Lyons L., Cohen F., Lyons R., Fedrigo-Fazio D., *Energy performance certificates in buildings and their impact on transaction prices and rents in selected EU countries*. European Commission (DG Energy), Paris 2013.
[16] Bottero M.C., Bravi M., *Valutazione dei benefici connessi al risparmio energetico degli edifici: un approccio econometrico*, "GEAM. GEOINGEGNERIA AMBIENTALE E MINERARIA", No. 3/2014, 15–24.
[17] De Ayala A., Galarraga I., Spadaro J.V., *The price of energy efficiency in the Spanish housing market*, "Energy Policy", Vol. 94/2016, 16–24.
[18] Marmolejo Duarte C., *La incidencia de la calificación energética sobre los valores residenciales: un análisis para el mercado plurifamiliar en Barcelona*, "Informes de la Construcción", Vol. 68/ 2016, Issue 543, 156.
[19] Yoshida J., Sugiura A., *Which "greenness" is valued? Evidence from green condominiums in Tokyo*, SSRN Working Paper, 2010.
[20] Burns M.C., Cladera J.R., Bergadà M.M., Seguí M.U., *El sistema metropolitano de la macrorregión de Madrid*, "Urban", No. 14/2009, 72.
[21] Marmolejo Duarte C., González Tamez C., *Does noise have a stationary impact on residential values?*, "Journal of European Real Estate Research", Vol. 2/2009, Issue 3, 259–279.
[22] Hope A.C.A., *A simplified Monte Carlo significance test procedure*, "Journal of the Royal Statistical Society. Series B (Methodological)", Vol. 30/1968, Issue 3, 582–598.
[23] Florio P., Teissier O., *Estimation of the energy performance certificate of a housing stock characterised via qualitative variables through a typology–based approach model: a fuel poverty evaluation tool*, "Energy and Buildings", Vol. 89/2015, 39–48.
[24] Ramos A., Labandeira X., Löschel A., *Pro–environmental households and energy efficiency in Spain*, "Environmental and Resource Economics", Vol. 63/2016, Issue 2, 367–393.

If you want to quote this article, its proper bibliographic entry is as follow: Chen A., Marmolejo-Duarte C., *Is the energy price premium spatially aggregated? A listing price analysis of the residential market in Barcelona*, Technical Transactions, Vol. 7/2018, pp. 5–20.