Ecological Economics 201 (2022) 107579

Contents lists available at ScienceDirect

Ecological Economics

journal homepage: www.elsevier.com/locate/ecolecon

The influence of housing location on energy ratings price premium in Alicante, Spain

Maria-Francisca Cespedes-Lopez *, V. Raul Perez-Sanchez, Raul-Tomas Mora-Garcia *

Universidad de Alicante, Carretera San Vicente del Raspeig s/n, 0369 San Vicente del Raspeig, Alicante, Spain

ARTICLE INFO

Keywords:
Multilevel models
Regression models
Housing price
Energy rating
Housing characteristics

ABSTRACT

Location is, along with other aspects, one of the most important characteristics when determining the sale or rental price of a residential property. Energy rating is one of the characteristics involved in determining the rent or sale price of a house. Past research has shown the importance of this attribute in numerous studies. Moreover, these studies have found mixed results regarding the magnitude, direction, and statistical significance of energy rating price premiums. This research aims to determine whether housing location influences energy rating price premium. To achieve this objective, a least squares regression model and a multilevel model were estimated using a sample of 70,170 different residences that were offered for sale in the province of Alicante. The multilevel models show that, once the differences due to the location (comarca) had been eliminated, the energy rating label itself had an effect on the asking price and also that there was an effect for the relationship of the energy rating with the location characteristics (comarca). On the other hand, the variables that defined the energy ratings were not those responsible for the differences between the average asking prices of the residences in the comarcas.

1. Introduction

The European Union (EU) has approved a series of Directives (The European Parliament and the Council of the European Union, 2003, 2010), which consequently have led to the implementation of a mandatory certification system called "EPC Rating", which classifies buildings according to their energy efficiency. A value scale was established according to the amount of energy consumed (kW/year-m^2) and/or CO_2 emissions, ranging from the letter "A" (best energy rating) to the letter "G" (worst energy rating). These Directives have two objectives. The first is to reduce the energy consumption of buildings. The second is to publicize the Energy Performance Certificate (EPC) of buildings or housing offered for sale or rent, in order to raise public awareness about energy consumption and increase the demand for energy-efficient buildings.

Since the approval of the Directives, a number of studies have been carried out with the objective of determining the price premiums generated by EPCs. These studies have shown that price premiums generated by energy ratings have found mixed results regarding the magnitude, direction, and statistical significance (Brounen and Kok, 2011; Cespedes-Lopez et al., 2020; Dell'Anna et al., 2019; Fuerst et al., 2015; Jensen et al., 2016; Marmolejo Duarte, 2016; Marmolejo Duarte and Chen, 2019; McCord et al., 2020).

The diversity of the results found in the literature led to the following research questions. Firstly, the fact that the results of previous research do not have a consistent trend, nor the same value, raises doubts regarding energy certification and its impact on price. Secondly, there are doubts regarding the methodology used as the majority of studies use Ordinary Least Squares (OLS) regression models, but no analysis technique has yet been used to structure the data in a hierarchical way with the purpose of analyzing the fixed and random effects that determine house prices. In short, it is not clear whether location influences the price premium generated by energy efficiency.

The main objective of this research was to analyze whether housing location influenced the price premium generated by a residence's energy rating. As a secondary objective, we looked to determine whether the energy ratings of residences in the province of Alicante were an influential characteristic in the asking price of housing at the comarca [1] level.

* Corresponding authors.
E-mail addresses: paqui.cespedes@ua.es (M.-F. Cespedes-Lopez), raul.perez@ua.es (V.R. Perez-Sanchez), rtmg@ua.es (R.-T. Mora-Garcia).

[1] Comarca is a division of territory comprising several municipalities, forming an intermediate level of administrative subdivision between the municipalities and the provinces.

https://doi.org/10.1016/j.ecolecon.2022.107579
Received 24 September 2021; Received in revised form 15 July 2022; Accepted 1 August 2022
Available online 19 August 2022

To this end, a regression model was estimated using ordinary least squares (OLS) and a hierarchical model with two levels: a) housing characteristics (level 1: housing); and b) location characteristics (level 2: comarca). At the same time, it was also analyzed, on the one hand, whether the location characteristics (level 2) significantly conditioned the asking price for housing, and on the other hand, whether housing characteristics (level 1) had a significant influence on the price of housing. The analysis was carried out on a specific case in the province of Alicante (Spain), using data from real estate offers for multifamily housing up for sale.

The first hypothesis (H1) was in regard to whether housing location characteristics affected the price premiums generated by the energy ratings. The second hypothesis (H2) was to determine whether the energy rating conditioned the asking price for housing in the province of Alicante at a comarca level.

The multilevel models show that, once the differences due to the location (comarca) had been eliminated, the energy rating label itself had an effect on the asking price and also that there was an effect for the relationship of the energy rating with the location characteristics (comarca). On the other hand, the variables that defined the energy ratings were not those responsible for the differences between the average asking prices of the residences in the comarcas.

This document is organized as follows: the second section presents a review of the literature. The third section denotes the materials and the methods used, outlining the sources that were employed and the dataset generated. The fourth section details the results. The fifth section offers a discussion of the results, and the sixth section summarizes the conclusions and policy implications.

2. Literature review

The study of the price premiums generated by EPCs for buildings is a current and highly relevant topic. There are many studies that have carried out exhaustive literature reviews, such as the works by Ankamah Yeboah and Rehdanz (2014); Brown and Watkins (2016); Cespedes-Lopez et al. (2019); Fizaine et al. (2018); Kim et al. (2017). These studies note a number of different issues to consider: 1) the type of energy certificate used (BREEAM, LEED, CASBEE, EPC rating, Minergie, NABERS, etc.) and its enforcement; 2) the location of the building (Europe, Asia, America, etc.); and 3) market segmentation (commercial or residential) and type of property (rental or sale).

As the scope of this paper is the analysis of price premiums for housing on sale with an "EPC rating" in the EU, we have focused our literature review on studies that have examined properties with these same characteristics. Although there are several studies that find the price premium to be positive and significant (Bonifaci and Copiello, 2015; Cornago and Dressler, 2020; de Ayala et al., 2016; Fuerst et al., 2013; Fuerst et al., 2015; Hyland et al., 2013; Marmolejo Duarte, 2016; Mudgal et al., 2013), negative and/or non-significant premiums have been found in other studies (Marmolejo Duarte and Chen, 2019; Olaussen et al., 2017; Stanley et al., 2016; Taltavull de la Paz et al., 2019). Table 1 shows the data from some of these works with the objective of showing the methodologies used and the results obtained in other studies.

3. Materials and methods

The research design is inductive, non-experimental, cross-sectional (Balluerka Lasa et al., 2002; Salkind, 1999; Tabachnick and Fidell, 2012), since the purpose of the study was to examine whether housing location influences the price premium generated by a residence's energy rating.

3.1. Data

3.1.1. Population and sample

The existing housing market in the Valencian Community is the third-largest in Spain, after Andalusia and Catalonia. Within the Valencian Community, Alicante is the province with the highest number of real estate transactions. From the 9142 transactions carried out in the third quarter of 2019, 7714 were existing homes (MITMA, 2020). This important activity is the reason for this territory being selected for analysis. In the study, a sample of the multifamily housing offered for sale in this province was used, which is divided into nine comarcas or zones.

One of the limitations when carrying out this type of study is due to the lack of information on real transaction prices and housing characteristics from official sources, being more common to have access to listing prices. Several authors suggest that real estate listing prices are an adequate substitute for transaction prices (Horowitz, 1992; Knight et al., 1998; Malpezzi, 2003; Shimizu et al., 2012). Other studies use listing price information from real estate portals due to the lack of information from other official sources (Agnew and Lyons, 2018; Bauer et al., 2013; Bian and Fabra, 2020; Brandt and Maennig, 2012; Copiello and Donati, 2021; Chasco Yrigoyen and Sánchez Reyes, 2012; Taruttis and Weber, 2022).

The information used for the creation of the dataset was mainly collected from the real estate portal idealista.com during the period between June 2017 and May 2018. A limiting factor of the research is the manual entry of the data by the property seller on the real estate portal idealista.com where the properties are published. The portal advertises properties even when the seller has not fully filled in all the characteristics (house size, number of bedrooms, etc.), which leads to missing values in the dataset.

Moreover, the data entry carried out by the seller may contain a high number of errors. As such, data pre-processing was performed in two phases: the elimination of observations with missing data and the elimination of observations with univariate outliers. In the first phase, observations with missing data in some of the variables were discarded, using the Listwise Deletion approach, mainly removing the properties that did not include the floor number, the state of the property, and whether it had an elevator. In this phase, the initial sample decreased from 97,077 to 70,989.

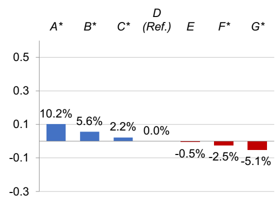
The second phase identified and eliminated the univariate outliers using the Simple Statistical Criterion (SSC) method. Using this method, five standard deviations of the set of values were established as the upper and lower limits of the data and those found outside this highly conservative confidence interval were eliminated (Aggarwal, 2013; Mariani et al., 2021). The final sample contained 70,170 observations from different households.

The representativeness of the sample was verified using the equation for large or infinite populations (Johnson and Kuby, 2011), using a confidence level of 95% ($z_{\alpha/2} = 1.96$), a probability level of $p = 0.50$, and a sample size of $n = 70{,}170$. A maximum error of 0.37% (0.0037) was estimated, which guaranteed a high statistical precision of the sample.

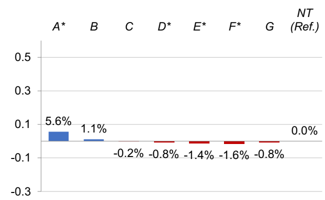
3.1.2. Information sources

To construct the dataset, several sources were used: 1) the real estate portal idealista.com was used to collect information regarding asking prices and housing characteristics; 2) data from the Population and Housing Census of the Spanish National Institute of Statistics were used to compile the dependency ratio and the percentage of people with a university education by census tract (INE, 2011) and the gross household income for 2018 by census tract (INE, 2021); and 3) other sources such as the General Directorate of Cadastre (SEG, 2019), the National Geographic Institute (IGN, 2018), the Spanish Ministry of Education, Culture, and Sport (CECD, 2019), and the General Directorate of Organization, Evaluation and Patient Care of the Valencian Regional Ministry of Health. Distances between dwellings and points of interest were

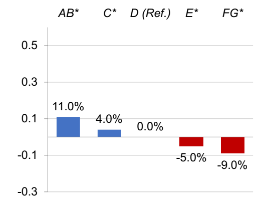
Table 1
Brief summary of the literature, detailing the studying, country, statistical model, the estimate concluded from the paper, and a graph showing the results.



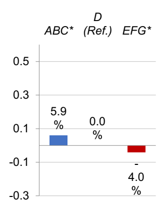
Paper: Brounen and Kok (2011)
Country: Netherlands
Model: OLS, estimation 2 (Table 3)



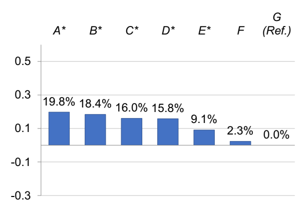
Paper: Chegut et al. (2016)
Country: Netherlands
Model: OLS, estimation 4 (Table 2)



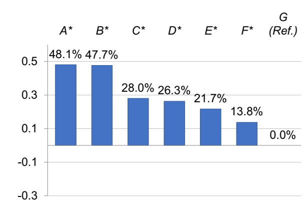
Paper: Notaries-France (2018)
Country: France (Nouvelle Aquitaine)
Model: OLS, estimation 2 (Fig. 2)



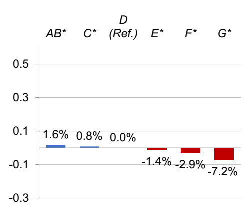
Paper: Ramos et al. (2015)
Country: Portugal
Model: OLS, estimation 2 (Table 5)



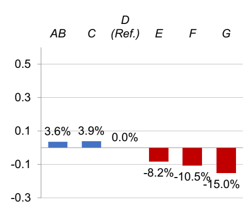
Paper: Bonifaci and Copiello (2015)
Country: Italy (Padua)
Model: OLS, estimation 1 (Table 2)



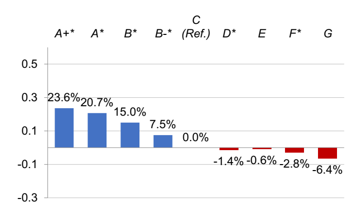
Paper: Copiello and Donati (2021)
Country: Italy (Padua)
Model: dynamic OLS, estimation 1 (Table 3).



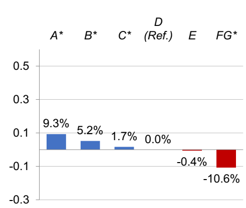
Paper: Fuerst et al. (2015)
Country: United Kingdom
Model: OLS, estimation 4 (Table 4)



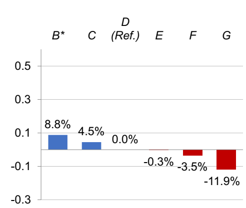
Paper: Fuerst et al. (2016)
Country: United Kingdom
Model: OLS, estimation 7 (Table 2)



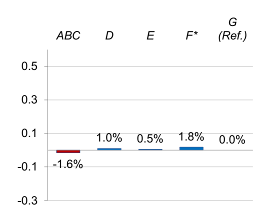
Paper: Evangelista et al. (2020)
Country: United Kingdom
Model: OLS, estimation 1 (Table 2)



Paper: Hyland et al. (2013)
Country: Ireland
Model: OLS, estimation 1 (Table 4)



Paper: McCord et al. (2020)
Country: Ireland (Belfast)
Model: OLS, estimation 2 (Table 6)



Paper: Taltavull de la Paz et al. (2019)
Country: Spain (Alicante)
Model: OLS, estimation 4 (Table 3)

Note: * indicates that the coefficient is statistically significant ($p \leq 0.05$).

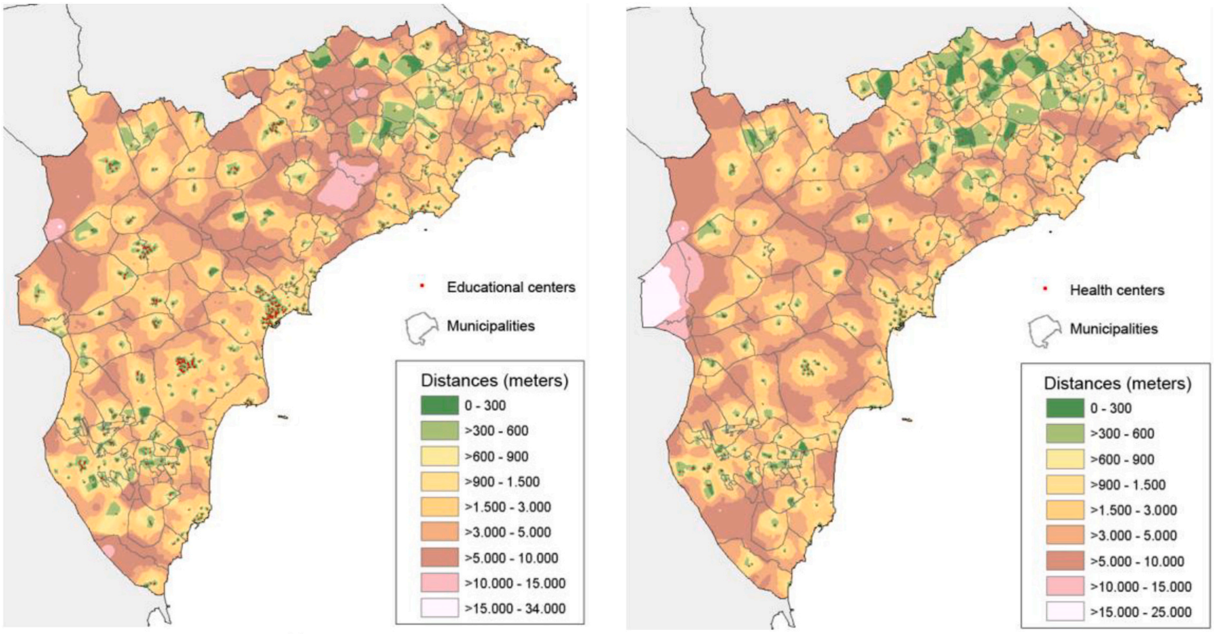
calculated by simulating the reality of the urban network: health centers, schools, town halls, parks, as well as proximity to the coast (Mora-Garcia, 2016), see Fig. 1.

3.1.3. Data description

In order to identify the variables that are used in this type of research, we selected 14 articles published between 2008 and 2020. These articles were all centered around identifying the price premium generated by energy ratings in multifamily housing for sale. These documents were analyzed and Fig. 2 shows the variables that were used on at least two occasions.

The information for all the variables used in previous studies was collected (Fig. 2), with the exception of four of them since they were not available (*highway accessibility, builder, distance train station,* and *building structure*). From the gathered information, a total of 40 variables were found. With these variables an initial ordinary least squares regression model was performed to identify statistically significant variables (OLS-0 in Table A1) and to test for collinearity between the variables. The variables *Age* and *Bedrooms* were discarded because they were not statistically significant, and the variable *University* was discarded because of a collinearity problem with the variables *Gross_income* and *Bajo_Segura.*

The energy rating characteristic was modeled using 8 dummy variables, 7 of which identified the letter of the energy certificate (A to G, using D as the reference letter), while the variable *Letter_NT* noted that the seller had not advertised the energy rating of the property. This



(a) (b)

Fig. 1. Distance maps to (a) educational centers, preschool and primary (*Dist_school*); and (b) health centers (*Dist_health*).

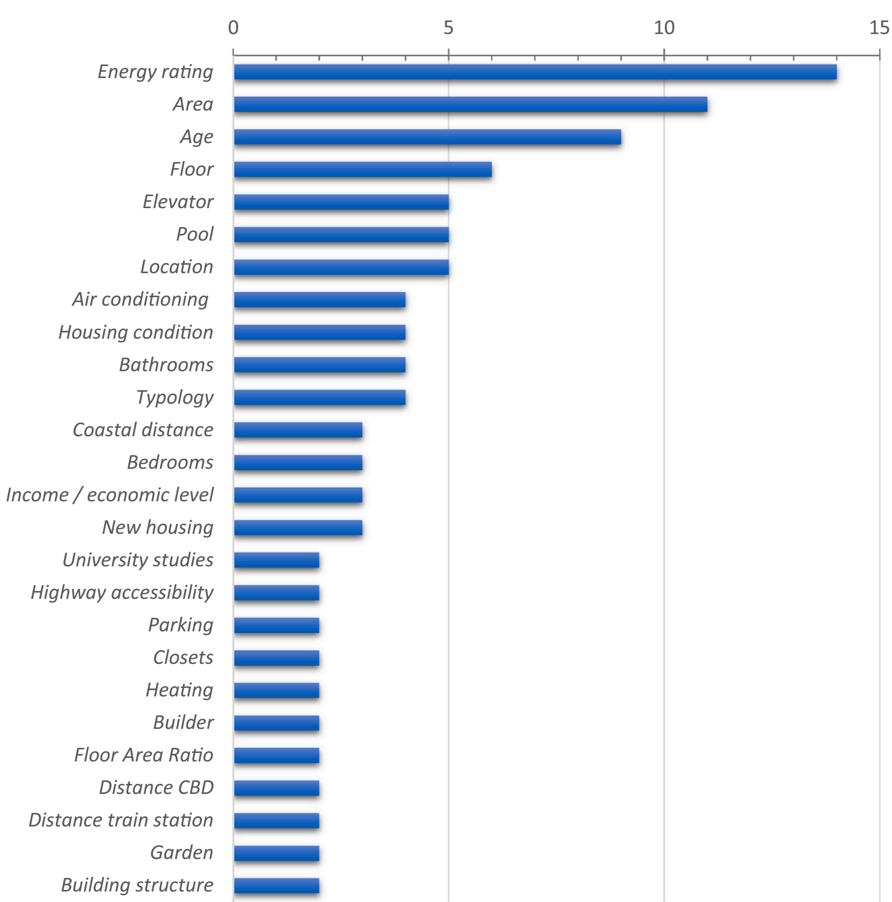


Fig. 2. Variables used by other authors to determine the price premiums generated by energy ratings in multi-family housing for sale. Note: Studies used to create the graph: Addae-Dapaah and Chieh (2011); Bian and Fabra (2020); Cajias and Piazolo (2013); Cespedes-Lopez et al. (2020); Dell'Anna et al. (2019); Deng et al. (2012); Fuerst and Shimizu (2016); Jayantha and Wan Sze (2013); Marmolejo Duarte (2016); Marmolejo Duarte and Chen (2019); Salvi et al. (2008); Shimizu (2010); Yoshida and Sugiura (2010); Zheng et al. (2012).

variable could be related indirectly to other letters since those properties without an energy rating in fact do have a letter between A and G, even though the seller had deliberately hidden it.

Following the recommendations of other authors (Cespedes-Lopez et al., 2019; Fizaine et al., 2018), letters have not been grouped and D (intermediate letter) is used as the reference letter. Using *Letter_NT* as the reference variable would have resulted in greater difficulty when interpreting the results, since it is not a category that excludes a specific

Table 2
Set of variables that make up the study with descriptive statistics.

Variable	Scale of measure	Description of the variables	Descriptive statistics				
			Media	*SD*	Min. Max.	Frequency	
Ln_Price	numerical	Dependent variable. The natural log of the property price offered by the seller (in Euro).	11.618	0.624	9.017 14.077		
		Level 1 independent variables (housing)					
Letter_A	dummy					(1) Letter A	1038
Letter_B	dummy					(1) Letter B	391
Letter_C	dummy					(1) Letter C	670
Letter_D	dummy	Indicates if the dwelling has an energy rating: letters A, B, C, D, E, F or G, or has no label (NT).				(1) Letter D	747
Letter_E	dummy					(1) Letter E	4157
Letter_F	dummy					(1) Letter F	1195
Letter_G	dummy					(1) Letter G	4281
Letter_NT	dummy					(1) No label	57,691
Apartment	dummy	Indicates whether the property has this typology Apartment (1 = yes).				(1) Apartment	62,549
Age	numerical	Age of the building (years), number of years that have passed since it was built.	33.443	12.193	1 95.4		
Area_m2	numerical	Built dwelling surface (sqm), gross square meters of the dwelling.	97.394	34.555	14 296		
Bedrooms	numerical	Number of bedrooms in the dwelling.	2.631	0.907	0 7		
Bathrooms	numerical	Number of bathrooms.	1.568	0.565	0 4		
Floor	numerical	Floor the dwelling was located on within the building.	3.080	2.802	0 19		
Closets	dummy	Availability of built-in closets (1 = yes).				(1) Closets	41,271
Air_conditioning	dummy	Availability of air conditioning (1 = yes).				(1) With	30,204
New_construction	dummy	Newly built housing that may be: a project, under construction, or <3 years old (1 = yes).				(1) New construction	628
State_to_renovate	dummy	Requires refurbishment (1 = yes).				(1) Renovate	4353
Elevator	dummy	Availability of elevator (1 = yes).				(1) With	51,334
Parking	dummy	Availability of garage slot (1 = yes).				(1) With	25,519
Pool	dummy	Availability of swimming pool (1 = yes).				(1) With	25,005
Garden	dummy	Availability of garden space (1 = yes).				(1) With	18,795
		Level 2 independent variables (comarca)					
Alicante	dummy					(1) Alicante	28,201
Alcoy	dummy					(1) Alcoy	1600
Alto_Vinalopo	dummy					(1) Alto Vinalopó	488
Bajo_Segura	dummy					(1) Bajo Segura	12,335
Bajo_Vinalopo	dummy	Identifier of the comarca: Alicante, Alcoy, Alto Vinalopó, Bajo Segura, Bajo Vinalopó, Condado, Marina Alta, Marina Baja and Medio Vinalopó.				(1) Bajo Vinalopó	8843
Condado	dummy					(1) Condado	241
Marina_Alta	dummy					(1) Marina Alta	7875
Marina_Baja	dummy					(1) Marina Baja	8459
Medio_Vinalopo	dummy					(1) Medio Vinalopó	2128
Coastal_region	dummy	Identification of property location within a coastal region.				(1) Coastal region	43,752
University	numerical	Percentage of the population with university studies.	17.147	10.356	0 54.650		
Dependency	numerical	Dependency ratio (sum of the population aged >64 and < 16 / population aged 16–64).	0.536	0.194	0.000 1.850		
Gross_income	numerical	Gross household income for 2018, in thousand euros.	30.724	9.904	13.392 82.776		
FAR	numerical	Floor Area Ratio (total building floor area/gross sector area), 150 m around the building, in m2 floor area/m2 sector area.	1.224	0.901	0.000 7.624		
Dist_park	numerical	Distance from the dwelling to the park, in km.	0.959	1.296	0.000 19.573		
Dist_health	numerical	Distance from the dwelling to the health center, in km.	1.153	1.363	0.000 18.857		
Dist_school	numerical	Distance from the dwelling to educational centers (preschool and primary), in km.	0.841	0.996	0.000 13.317		
Dist_municipality	numerical	Distance from the dwelling to the town hall of the municipality, in km.	2.134	1.774	0.013 12.458		

NOTE: Sample of 70,170 observations.

letter.

Table 2 shows the variables names, as well as their description, the scale of measure and descriptive statistics.

Regarding distance variables, the literature showed that the proximity of dwellings to green spaces, such as parks, positively affects children's development by improving their social interaction, motor skills and concentration (Kahn and Kellert, 2002; Kaplan and Kaplan, 1989). This positive effect was also observed in elderly people, improving their social integration, well-being and longevity (Kweon et al., 1998). In addition, these two population groups have in common that they are the users who demand more primary care in health centers (Giraldo Osorio and Vélez Álvarez, 2014; Ministerio de Sanidad, 2021),

Table 3
Price descriptions in each of the comarcas.

Comarca		Precio (€)		
Designation	Count	Mean	*SD*	Coef. of Variation
Alicante	28,201	150,269	100,792	67.1%
Alcoy	1600	77,471	50,654	65.4%
Alto Vinalopó	488	76,529	42,429	55.4%
Bajo Segura	12,335	98,583	58,484	59.3%
Bajo Vinalopó	8843	108,918	64,847	59.5%
Condado	241	87,303	44,695	51.2%
Marina Alta	7875	166,018	96,734	58.3%
Marina Baja	8459	164,596	104,123	63.3%
Medio Vinalopó	2128	70,761	39,778	56.2%
TOTAL	70,170	134,666	92,492	68.7%

and schools in the case of children. These positive effects, caused by external sources, can be combined with other indoor qualities of the dwelling, such as high energy rating, and can be valued by people considering the purchase of a dwelling. Therefore, in this paper we have considered the interaction of the energy rating variable with the distances to these important points of the urban fabric, in order to analyze whether dwellings with better ratings, in principle with better construction characteristics, interact with these services offered by the city.

Table 3 offers descriptive information regarding the average of the asking price and the standard deviation of the price in each of the comarcas. The average of the asking prices between the comarcas ranged from 70,761€ for Medio Vinalopó and 166,018€ for Marina Alta, showing a priori a relationship between prices and the comarca where the property is located.

3.2. *Statistical modeling*

To measure the impact of energy rating on prices, in this paper we estimated the models without performing any letter grouping. As a reference variable, and as Cespedes-Lopez et al. (2019); Fizaine et al. (2018) suggest, residences with an intermediate rating (letter D, variables $\beta_{Ref.letter}$ $\Upsilon_{Ref,0}$) were used. These models were estimated by using the statistical package SPSS for Windows version 25 (IBM Corp, 2016).

3.2.1. *Regression model by OLS*

The regression model was estimated using ordinary least squares (OLS), and its specification had a semilogarithmic form according to the following expression:

$$ln(\gamma_i) = \beta_0 + \sum_{k=1}^{n} \beta_k X_{ik} + e_i \tag{1}$$

where:

$ln\ (\gamma_i)$ is the natural log of the asking price for housing "*i*".

β_0 is the fixed component, it does not depend on the market.

β_k is the parameter to estimate related to the characteristic "*k*".

X_{ik} is the continuous variable that collects the characteristic "*k*" of the observation "*i*".

e_i is the error term in the observation "*i*".

The functional form chosen was semilogarithmic, as it facilitated the interpretation of the coefficients and minimized the problem of heteroscedasticity (Kain and Quigley, 1975; Malpezzi, 2003).

3.2.2. *Multilevel model*

Multilevel models are used in research projects where the data are structured in a hierarchical way and are characterized by the fact that the lower level observations are related to the higher level one (Heck et al., 2012; Martínez Garrido and Murillo Torrecilla, 2013). This type of analysis allows researchers to examine the influence of independent variables at different levels on a phenomenon (Merino Noé, 2017) by providing information on what percentage of variance is explained at each of the levels. According to Acevedo Álvarez (2008), there are no other statistical analyses that allow for the individual, collective, and crosswise analysis of all variables involved, which, at the same time, also provide information on fixed parameters, random parameters, variance, and covariance. The main advantage this type of analysis has over other more traditional models is that it allows for more accurate predictions of the data (De la Cruz, 2008; Gelman, 2006; Osborne, 2000).

The real estate market has a hierarchical structure, since residences are integrated within a building, buildings belong to a neighborhood, neighborhoods make up localities, localities are included in comarcas, comarcas make up part of provinces, provinces constitute autonomous regions, and communities belong to a country. Therefore, residences belonging to the same building have similar characteristics, which vary to a greater or lesser extent depending on the building, neighborhood, locality, comarca, province, or autonomous regions. As such, housing characteristics are data with a hierarchical structure, which is noted by authors such as Brown and Uyar (2004); Cichulska and Cellmer (2018); Jones and Bullen (1994); Kiel and Zabel (2008); Raudenbush and Bryk (2002), and therefore, they can be analyzed using multilevel models.

The hierarchical structure of the data made it advisable to analyze them using a two-level multilevel model as shown in Fig. 3: level 1 (housing) and level 2 (comarca).

As indicated by Murillo Torrecilla (2008), multilevel models are applications of classical regression models, through which different regression models are developed for each level. The first-level models are related to a second-level model, in which the regression coefficients of the first level are regressed on a second level as explanatory variables, with the process being repeated for the different existing levels. In this work, level 2 consisted of the comarcas, with the variables of this level being the same for all the residences belonging to the same comarca. Level 1 consisted of the residences, with variables varying according to the characteristics of each residence. With the two levels defined, the multilevel models made it possible to simultaneously examine the influence of the location (level 2, comarca) and individual differences (level 1, housing) on the prices offered for housing.

The statistical modeling process was carried out in five steps (Table 4 and Fig. 4): 1) null model; 2) regression of means as a result (RMR); 3) random-effects covariance analysis (RECA); 4) random coefficient regression analysis (RCRA); and 5) regression analysis of means and

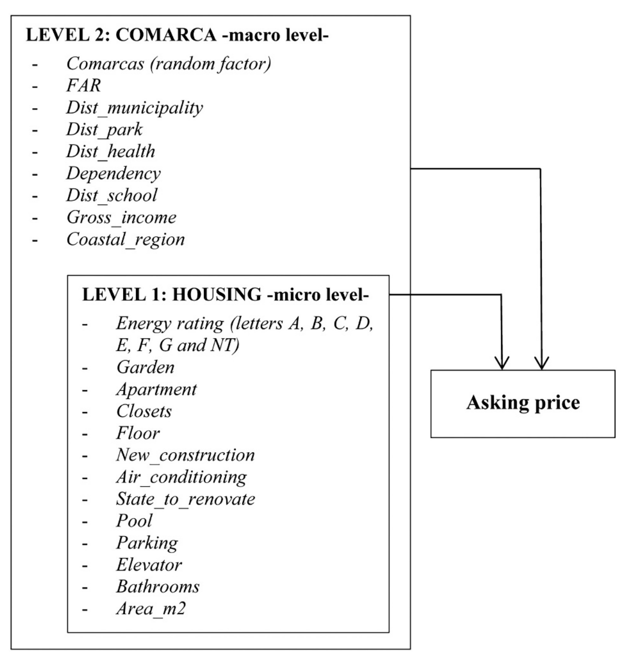


Fig. 3. Diagram of the multilevel model, with the levels and variables to be analyzed.

Table 4
Specification of the multilevel models, according to the steps performed in the modeling process.

Step		Model broken down by level	Multilevel models	
1	N1 N2	$ln(Y_{ij}) = \beta_{0j} + e_{ij}$ $\beta_{0j} = \Upsilon_{00} + u_{0j}$	Null model: $ln(Y_{ij}) = \Upsilon_{00} + (u_{0j} + e_{ij})$	(2)
2	N1 N2	$ln(Y_{ij}) = \beta_{0j} + e_{ij}$ $\beta_{0j} = \Upsilon_{00} + \sum_{k=1}^{n} \Upsilon_{0k} z_{jk} + u_{0j}$	Regression of Means as a Result (RMR): $ln(Y_{ij}) = \Upsilon_{00} + \sum_{k=1}^{n} \Upsilon_{0k} z_{jk} + (u_{0j} + e_{ij})$	(3)
3	N1 N2	$ln(Y_{ij}) = \beta_{0j} + \beta_{1j} x_{ijl} + e_{ij}$ $\beta_{0j} = \Upsilon_{00} + \sum_{k=1}^{n} \Upsilon_{0k} z_{jk} + u_{0j}$ $\beta_{1j} = \sum_{l=1}^{m} \Upsilon_{l0}$	Random-Effects Covariance Analysis (RECA): $ln(Y_{ij}) = \Upsilon_{00} + \sum_{k=1}^{n} \Upsilon_{0k} z_{jk} + \sum_{l=1}^{m} \Upsilon_{l0} x_{ijl} + (u_{0j} + e_{ij})$	(4)
4	N1 N2	$ln(Y_{ij}) = \beta_{0j} + \beta_{1j} x_{ijl} + \beta_{2j} x_{ij,\ letter} + e_{ij}$ $\beta_{0j} = \Upsilon_{00} + \sum_{k=1}^{n} \Upsilon_{0k} z_{jk} + u_{0j}$ $\beta_{1j} = \sum_{l=1}^{m} \Upsilon_{l0}$ $\beta_{2j} = \sum_{letter=1}^{7} \Upsilon_{letter,0} + u_{letter,j}$	Random Coefficient Regression Analysis (RCRA): $ln(Y_{ij}) = \Upsilon_{00} + \sum_{k=1}^{n} \Upsilon_{0k} z_{jk} + \sum_{l=1}^{m} \Upsilon_{l0} x_{ijl} + \sum_{letter=1}^{7} \Upsilon_{letter,k} x_{ij,letter} + (u_{0j} + u_{letter,j} x_{ij,letter} + e_{ij})$	(5)
5	N1 N2	$ln(Y_{ij}) = \beta_{0j} + \beta_{1j} x_{ijl} + \beta_{2j} x_{ij,\ letter} + e_{ij}$ $\beta_{0j} = \Upsilon_{00} + \sum_{k=1}^{n} \Upsilon_{0k} z_{jk} + u_{0j}$ $\beta_{1j} = \sum_{l=1}^{m} \Upsilon_{l0}$ $\beta_{2j} = \sum_{k=1}^{n} \sum_{letter=1}^{7} \Upsilon_{letter,k} z_{jk} + u_{letter,j}$	Regression Analysis of Means and Slopes as Result (RAMSR): $ln(Y_{ij}) = \Upsilon_{00} + \sum_{k=1}^{n} \Upsilon_{0k} z_{jk} + \sum_{l=1}^{m} \Upsilon_{l0} x_{ijl} + \sum_{k=1}^{n} \sum_{letter=1}^{7} \Upsilon_{letter,k} z_{jk} x_{ij,letter} + (u_{0j} + u_{letter,j} x_{ij,letter} + e_{ij})$	(6)

slopes as result (RAMSR). These models were estimated using restricted maximum likelihood (REML) to avoid biased estimates (Alarcón et al., 2015; Pérez Fernández, 2012; Tuero Herrero, 2013). They had a semi-logarithmic specification and were reordered by grouping fixed effects at the beginning (Υ_{00}, Υ_{01}, Υ_{10}…) and random effects at the end ($u_{0j} + u_{letter,\ j} x_{ijl} + e_{ij}$) (Alarcón et al., 2015; Pardo et al., 2007; Tuero Herrero, 2013). Random effects are coefficients that take their values according to a probability function, therefore they have a mean and a variance (Montero Granados, 2011; Pérez Fernández, 2012).where:

$ln(Y_{ij})$ is the natural log of the dependent variable -asking price- for the residence "*i*" in the comarca "*j*".

β_{0j} is the fixed component; it represents the mean of the dependent variable of the comarca "*j*".

Υ_{00} indicates the mean value of the dependent variable for all the comarcas.

Υ_{0k} indicates the main effect (parameter) of the predictor variable "*Z*" of the comarca level (level 2) on the intercept. Where "*k*" indicates the number of the predictor variable.

Z_{jk} is the predictor variable at the comarca level (level 2) that collects on characteristic "*Z*" in comarca "*j*". Where "*k*" indicates the number of the predictor variable.

u_{0j} is the random factor of the average of the dependent variable in comarca "*j*".

β_{1j} is the slope or regression coefficient; it represents the change that is predicted by the model in the dependent variable for residence "*i*" in comarca "*j*".

Υ_{l0} is the main effect (parameter) of the predictor variable "X" of the housing level (level 1) on the intercept. Where "*l*" indicates the number of the predictor variable.

$u_{letter,\ j}$ is the random factor of the slope of the dependent variable for the characteristic energy rating in comarca "*j*". Where subscript letter = 1 refers to letter A; letter =2 to letter B; letter =3 to letter C; letter =4 to letter E; letter =5 to letter F; letter =6 to letter G; and letter =7 to letter NT.

X_{ijl} is the housing level predictor variable (level 1) that captures the characteristic "X" for residence "*i*" in comarca "*j*". Where "*l*" indicates the number of the predictor variable.

β_{2j} is the slope or regression coefficient, for the characteristic energy rating in comarca "*j*".

$\Upsilon_{letter,\ 0}$ is the main effect (parameter) of the characteristic "energy rating" of the housing level (level 1) on the intercept. Where subscript letter = 1 refers to letter A; letter =2 to letter B; letter =3 to letter C; letter =4 to letter E; letter =5 to letter F; letter =6 to letter G; and letter =7 to letter NT.

$X_{ij,\ letter}$ is the housing level predictor variable (level 1) that captures the characteristic "energy rating" for residence "*i*" in comarca "*j*". Where subscript letter = 1 refers to letter A; letter =2 to letter B; letter =3 to letter C; letter =4 to letter E; letter =5 to letter F; letter =6 to letter G; and letter =7 to letter NT.

e_{ij} It is the error term of residence "*i*" in comarca "*j*", which is an error assumed to be normally distributed with zero mean and equal variance σ_e^2 in all comarcas.

In the first step, a random effects analysis of variance (ANOVA) or null model (Table 4 eq. (2)), was estimated without including the explanatory variables. This model defined what part of the difference in the asking price for the residences was due to differences between comarcas and what part was a consequence of the characteristics of the residence itself.

In the second step, the RMR model was estimated (Table 4 eq. (3)), where the eight level 2 predictors were introduced sequentially (k = 1, …,8) -comarca- (*FAR, Dist_municipality, Dist_park, Dist_health, Dependency, Dist_school, Gross_income and Coastal_region*), in order to determine the variability of level 2.

In the third step, the RECA model was estimated (Table 4 eq. (4)), where all level 1 predictors were entered sequentially (l = 1, …,19) -housing- (*Letter_A, Letter_B, Letter_C, Letter_E, Letter_F, Letter_G, Letter_NT, Garden, Apartment, Closets, Floor, New_construction, Air_conditioning, State_to_renovate, Pool, Parking, Elevator, Bathrooms and Area_m2*), as well as those of level 2 (k = 1, …,8) -comarca- (*FAR, Dist_municipality, Dist_park, Dist_health, Dependency, Dist_school, Gross_income and Coastal_region*), in order to determine which variables defined the variability of level 1 and both levels (level 1 and 2). This model is similar to the OLS regression model.

In the fourth step, the RCRA model was estimated (Table 4 eq. (5)) to determine how much of the variability between comarcas depended on the energy rating characteristic. To this end, an estimate was made for each comarca and for each letter ($\beta_{2j} x_{ij,\ letter}$). This assumes that not only did the comarcas have different average prices but also that the relationship between the asking price and the energy rating may not have been the same in all the comarcas (different slopes). Seven estimations of the eq. (5) were made, with one being done for each random coefficient. This revealed, by random coefficient, each of the variables that defined the energy rating characteristic (letters A, B, C, E, F, G, and NT), with the exception of the residences that had a letter D as the reference letter. As a result, models M36, M44, M52, M60, M68, M76, and M84, (Table A4) were created, as shown in Fig. 4.

In the fifth and final step, the RAMSR model (Table 4 eq. (6)) was estimated with the goal of estimating which level 2 (comarca) predictors

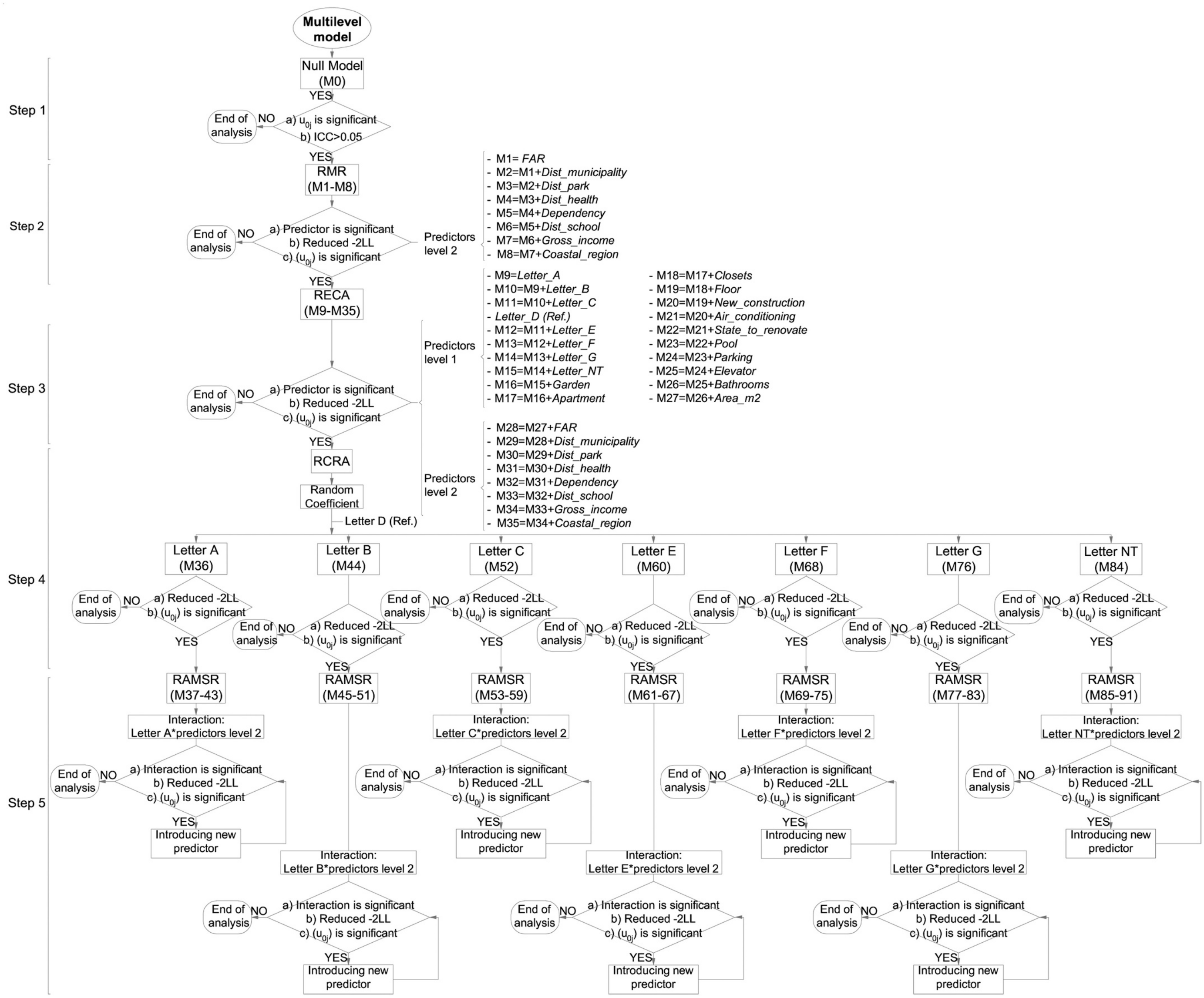


Fig. 4. Diagram of the steps used in the construction of the model and estimation process.

influenced each of the variables that determined the energy rating characteristic (letters A, B, C, E, F, G, and NT). To this end, new predictors were generated. These were the result of performing the interaction of each of the letters (A, B, C, E, F, G, and NT) with each of the level 2 predictors (k = 1, …,8) -comarca- (*FAR, Dist_municipality, Dist_park, Dist_health, Dependency, Dist_school, Gross_income and Coastal_region*) (Fig. 4). These new predictors were introduced sequentially, as in the previous cases.

The null model (Table 4 eq. (2)) had two objectives. The first was to determine whether the data were hierarchical in nature and whether the use of a multilevel model was appropriate. To this end, three conditions needed to have been met: a) the average price between comarcas needed to have been different; b) the variance of the comarca (u_{0j}) needed to have been statistically significant; and c) the intraclass correlation coefficient (ICC) needed to have indicated that the comarcas and the residences were related to each other and were not independent, that is, the ICC needed to have had a value >0.05 (Alarcón et al., 2015). The ICC was an indicator of the homogeneity of the groups. It expressed the total explained variance due to the comarca, and was calculated according to the expression (7). The second objective of the study was to use the null model as a reference to evaluate the goodness of fit of more complex conditional models (RMR, RECA, RCRA, and RAMSR).

$$\rho = \frac{\sigma_u^2}{\sigma_u^2 + \sigma_e^2} \tag{7}$$

where:

ρ is the total variance explained.

σ_u^2 is the variance in the comarca (level 2), u_{0j}.

σ_e^2 is the variance of the error associated with each individual prediction of the model, e_{ij}.

The RMR, RECA, RCRA, and RAMSR models had a hierarchical approach in identifying the predictors that influenced the asking price, therefore, to include a predictor in these models the following needed to have been met: a) the predictor needed to have be statistically significant (*t*-statistic); b) introducing each new predictor needed to have reduced the deviance (−2LL statistic) with respect to the previous model; and c) the estimates of the covariance parameters needed to have been significant, as determined using the Wald test (Wald, 1943).

Table 5
Summary of the results of the OLS regression model without interactions (OLS-1) and with interactions (OLS-2). (The complete results of the OLS-1 model are shown in Table A2 of the Appendix.)

Coefficient	Variable	OLS-1 without interactions		OLS-2 with interactions	
		Non-standardized coefficients		Non-standardized coefficients	
		B	*SE*	B	*SE*
β_0	Interception	9.762***	0.015	9.759***	0.019
β_1	*Letter_A*	0.002	0.016	0.000	0.016
β_2	*Letter_B*	−0.078***	0.020	−0.078***	0.020
β_3	*Letter_C*	0.009	0.017	0.043*	0.022
$\beta_{Ref.letra}$	*Letter_D (Ref.)*				
β_4	*Letter_E*	−0.097***	0.013	−0.122***	0.016
β_5	*Letter_F*	−0.090***	0.015	−0.117***	0.018
β_6	*Letter_G*	−0.125***	0.013	−0.138***	0.023
β_7	*Letter_NT*	−0.032**	0.012	−0.024	0.017
β_8	*Apartment*	−0.047***	0.004	−0.046***	0.004
β_9	*Area_m2*	0.006***	0.000	0.006***	0.000
β_{10}	*Bathrooms*	0.229***	0.003	0.228***	0.003
β_{11}	*Floor*	0.007***	0.000	0.007***	0.000
β_{12}	*Closets*	0.036***	0.003	0.035***	0.003
β_{13}	*Air_conditioning*	0.083***	0.003	0.082***	0.003
β_{14}	*New_construction*	0.250***	0.013	0.250***	0.013
β_{15}	*State_to_renovate*	−0.177***	0.005	−0.177***	0.005
β_{16}	*Elevator*	0.223***	0.003	0.222***	0.003
β_{17}	*Parking*	0.121***	0.003	0.121***	0.003
β_{18}	*Pool*	0.111***	0.004	0.112***	0.004
β_{19}	*Garden*	0.026***	0.004	0.028***	0.004
$\beta_{Ref.Comarca}$	*Alicante (ref.)*				
β_{20}	*Alcoy*	−0.228***	0.009	−0.226***	0.009
β_{21}	*Alto_Vinalopo*	−0.112***	0.015	−0.106***	0.015
β_{22}	*Bajo_Segura*	−0.064***	0.005	−0.063***	0.005
β_{23}	*Bajo_Vinalopo*	0.043***	0.004	0.043***	0.004
β_{24}	*Condado*	−0.113***	0.021	−0.115***	0.021
β_{25}	*Marina_Alta*	0.123***	0.005	0.124***	0.005
β_{26}	*Marina_Baja*	0.187***	0.005	0.187***	0.005
β_{27}	*Medio_Vinalopo*	−0.217***	0.008	−0.214***	0.008
β_{28}	*Coastal_region*	0.296***	0.003	0.287***	0.008
β_{29}	*Dependency*	0.202***	0.007	0.227***	0.018
β_{30}	*Gross_income*	0.012***	0.000	0.012***	0.000
β_{31}	*FAR*	−0.013***	0.002	−0.013***	0.002
β_{32}	*Dist_park*	−0.011***	0.001	−0.011***	0.001
β_{33}	*Dist_health*	0.011***	0.001	0.016***	0.003
β_{34}	*Dist_school*	0.062***	0.002	0.061***	0.002
β_{35}	*Dist_municipality*	−0.007***	0.001	−0.012***	0.003
β_{36}	*Letter_C*Dist_health*			−0.036**	0.013
β_{37}	*Letter_E*Dist_municipality*			0.012**	0.004
β_{38}	*Letter_F*Dist_health*			0.021**	0.008
β_{39}	*Letter_G*Dist_municipality*			0.010*	0.005
β_{40}	*Letter_G*Dist_health*			0.013*	0.006
β_{41}	*Letter_G*Dependency*			−0.133***	0.033
β_{42}	*Letter_G*Dist_school*			0.029***	0.007
β_{43}	*Letter_G*Coastal_region*			0.068***	0.013
β_{44}	*Letter_NT*Dist_municipality*			0.004	0.003
β_{45}	*Letter_NT*Dist_health*			−0.007*	0.003
β_{46}	*Letter_NT*Dependency*			−0.022	0.020
β_{47}	*Letter_NT*Coastal_region*			0.005	0.008
	N	70,170		70,170	
	R^2	0.725		0.726	
	Adjusted R^2	0.725		0.726	
	SE of the estimation	0.327		0.327	
	F	5292.561		2044.249	
	p	0.000		0.000	
	Durbin-Watson	1.854		1.858	

NOTES: dependent variable *Ln_price*; signification: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$; *SE*: Standard Error.

4. Results

4.1. Regression model (OLS)

Table 5 shows the results obtained for the regression model estimated by OLS without interactions (OLS-1) and with interactions (OLS-2). The same interactions are included in the OLS-2 model as in the multilevel model, so that the results of the estimations can be compared. Regarding the energy rating of the residences, in the OLS-2 model, all values were statistically significant with the exception of the residences that had an advertised letter of A and residences that do not advertise their rating (*Letter_NT*). This model estimated that residences with a letter A, B, C, E, F, G, or no advertised rating (*Letter_NT*) had a premium in the asking price of 0.0%, −7.8%, 4.3%, −12.2%, −11.7%, −13.8%, and − 2.4%, respectively, with respect to the reference (letter D).

It was verified that the data were in line with the assumptions made regarding normality and heteroscedasticity. This was done by analyzing the graphs regarding normality and regarding the predicted value of the

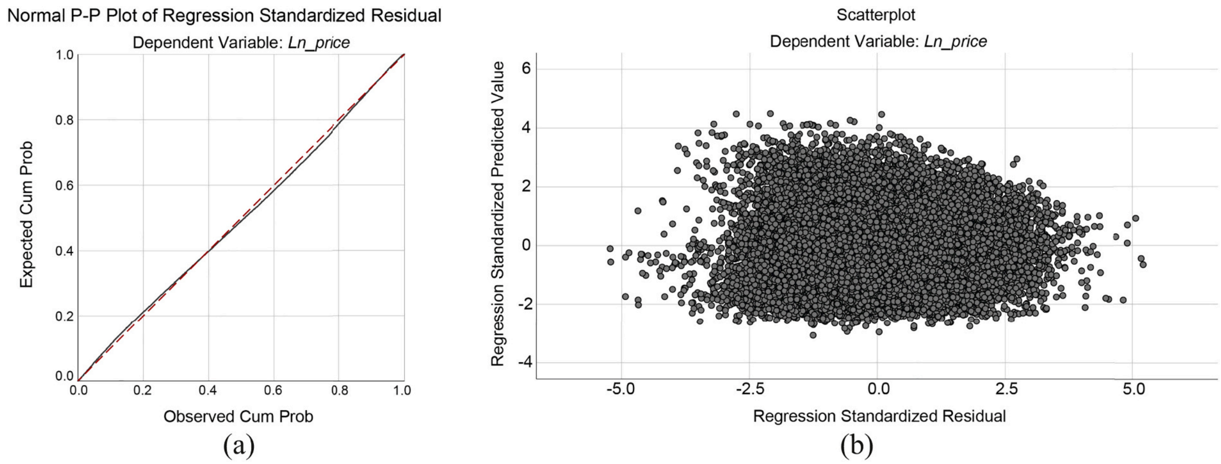


Fig. 5. (a) Normality plots and (b) predicted value of residuals.

Table 6
Summary of null model results, eq. (2).

Fixed effects estimates								
Parameter		Estimate	*SE*	*df*	*t*	*Sig.*	*CI* 95% Lower limit	*CI* 95% Upper limit
Υ_{00}	Intercept	11.412	0.113	8.014	100.495	0.000	11.151	11.674

Covariance parameter estimates						
Parameter	Estimate	*SE*	Wald *Z*	*Sig.*	*CI* 95% Lower limit	*CI* 95% Upper limit
Residual (e_{ij})	0.334	0.0018	187.298	0.000	0.331	0.338
Comarca variance (u_{0j})	0.116	0.0580	1.997	0.046	0.043	0.309
Deviance ($-2LL$)	122,351.459					
AIC Criterion	122,355.459					
BIC Criterion	122,373.776					

NOTES: dependent variable *Ln_Price*; *SE*: Standard Error; *df*: degrees of freedom; *CI*: Confidence interval.

residuals. In view of these graphs (Fig. 5), it was noted that the sample had a normal distribution and no serious problems of heteroscedasticity were evident.

Regarding the energy rating variables, the *Letter_NT* category (properties that did not publish the energy rating) had a *VIF* of 13.942 (Table A2). This high VIF value is due to the existence of multicollinearity of the *Letter_NT* category with other letters, since the dwelling coded as *Letter_NT* will in reality have some energy rating between A and G. As suggested by Allison (1977, 2012), there are some situations in which a high *VIF* is not a problem and can be ignored. One of those cases is when the model has dummy variables with more than three categories and the reference category has few cases. The other variables show *VIF* variables of between 1.025 and 2.236, which are entirely acceptable when presented with values <2.5 as suggested by Allison (1998).

4.2. Multilevel model

The results of the null model (Table 6) showed that the estimate of the average asking price in the comarca ($\Upsilon_{00} = 11.412$ which is equivalent to 90,400 €) differed from zero and was statistically significant ($p = 0.000$). Additionally, there were statistically significant differences in the asking price of residences within the comarcas ($u_{0j} = 0.116$; $p = 0.046$), as well as in their average asking price across comarcas ($e_{ij} = 0.334$; $p = 0.000$). In addition, the ICC had a value of 0.257 (Table 7), indicating that 25.7% of the total variance of the asking price was attributable to the variables that defined the comarcas (level 2). This made it advisable to perform a multilevel analysis.

Following the classification shown in Fig. 3, the predictors were introduced sequentially in the different models according to the importance of the predictor, which in this case was taken as a function of the value obtained for the standardized beta coefficient of the OLS-1 regression (Table A1). This procedure was not performed with the energy rating nor with the comarca. In the first case, this was because it was the characteristic being analyzed, and in the second, it was because it was the random factor.

Following this strategy, at level 1 (housing) the order adopted was as follows: the variables referring to the energy rating (letters A, B, C, E, F, G, and NT) were first, then the order taken was as follows: *Garden*, *Apartment*, *Closets*, *Floor*, *New_construction*, *Air_conditioning*, *State_to_renovate*, *Pool*, *Parking*, *Elevator*, *Bathrooms* and *Area_m2*. At level 2 (comarca), the order taken was as follows: *FAR*, *Dist_municipality*, *Dist_park*, *Dist_health*, *Dependency*, *Dist_school*, *Gross_income* and *Coastal_region*. Table 7 shows a summary of the results of the comparison of the null model and the rest of the multilevel models (RMR, RECA, RCRA, and RAMSR), Table A3 shows the complete results. This table shows the model designation, the variables introduced in the model, the deviance (-2LL), the difference between the deviance of the previous model and the model in question, the significance of the variable introduced (*t*-statistic), the variance of the comarca with its significance according to the Wald statistic, the variance of the residual, the ICC, and the explained variance of each model. The Table A3 also shows the models

Table 7
Comparison of the null model with the rest of the multilevel models (all steps and results are shown in Table A3 of the Appendix).

Designation	Variables	−2LL	Difference (−2LL)	*t* (*p*)	Comarca variance (u_{0j}) Wald Z (*p*)	Comarca variance (u_{0j}) Estimate	Residual variance (e_{ij})	ICC	Variance explained
STEP 1: Null Model (without variables)									
M0		122,351.459		125.712 (0.000)	1.995 (0.046)	0.116	0.334	0.257	
STEP 2a: RMR, with level 2 predictor variables									
M8	M7 + *Coastal_region*	100,523.036	4474.613	68.069 (0.000)	1.993 (0.046)	0.037	0.245	0.132	0.679
STEP 2b: RMR, with level 1 predictor variables									
M27	M26 + *Area_m2*	61,322.99	11,118.649	109.861 (0.000)	1.997 (0.046)	0.054	0.140	0.280	0.530
STEP 3: RECA, with level 1 and 2 predictor variables									
M35	M34 + *Coastal_region*	42,620.138	8515.231	95.229 (0.000)	1.994 (0.046)	0.021	0.107	0.162	0.821
STEP 4: RCRA, with level 1 and 2 predictor variables taking energy ratings as a random coefficient (letters A, B, C, E, F, G, and NT). STEP 5: RAMSR, with level 1 predictor variables, level 2 predictor variables and the interactions of the energy ratings (letters A, B, C, E, F, G and NT) with the level 2 variables, taking each letter as a random coefficient.									
STEP 5c: RAMSR, interaction of the letter C with the level 2 variables, taking the letter C as the random coefficient.									
M55	M52 + *Letter_C*Dist_health*	42,597.766	2.425	−3.058 (0.000)	1.994 (0.046)	0.021	0.107	0.163	0.820
STEP 5d: RAMSR, interaction of the letter E with the level 2 variables, taking the letter E as the random coefficient.									
M61	M60 + *Letter_E*Dist_municipality*	42,588.235	1.982	3.443 (0.000)	1.994 (0.046)	0.021	0.107	0.163	0.820
STEP 5e: RAMSR, interaction of the letter F with the level 2 variables, taking the letter F as the random coefficient.									
M71	M68 + *Letter_F*Dist_health*	42,604.654	0.236	2.869 (0.000)	1.994 (0.046)	0.021	0.107	0.163	0.819
STEP 5f: RAMSR, interaction of the letter G with the level 2 variables, taking the letter G as the random coefficient.									
M77	M76 + *Letter_G*Dist_municipality*	42,493.687	27.228	6.075 (0.000)	1.994 (0.046)	0.020	0.107	0.155	0.831
M79	M77 + *Letter_G*Dist_health*	42,485.997	7.690	4.070 (0.000)	1.994 (0.046)	0.020	0.107	0.155	0.830
M80	M79 + *Letter_G*Dependency*	42,472.958	13.039	−4.286 (0.000)	1.994 (0.046)	0.020	0.107	0.155	0.830
M81	M80 + *Letter_G*Dist_school*	42,464.740	8.218	4.023 (0.000)	1.994 (0.046)	0.020	0.107	0.156	0.830
M83	M81 + *Letter_G*Coastal_region*	42,443.549	21.191	5.371 (0.000)	1.994 (0.046)	0.020	0.107	0.158	0.827
STEP 5g: RAMSR, interaction of the letter NT with the level 2 variables, taking the letter NT as the random coefficient.									
M85	M84 + *Letter_NT*Dist_municipality*	42,445.095	14.918	−5.068 (0.000)	1.974 (0.048)	0.019	0.107	0.150	0.838
M87	M85 + *Letter_NT*Dist_health*	42,440.196	4.899	−3.849 (0.000)	1.975 (0.048)	0.019	0.107	0.149	0.839
M88	M87 + *Letter_NT*Dependency*	42,438.170	2.026	2.889 (0.000)	1.974 (0.048)	0.019	0.107	0.149	0.839
M91	M88 + *Letter_NT*Coastal_region*	42,429.714	8.456	−4.089 (0.000)	1.974 (0.048)	0.017	0.107	0.137	0.854

with predictors that were discarded because they did not meet any of the conditions mentioned above (Fig. 4). By comparing the variance parameter estimates of the null model (M0) with the others, the percentage of variance explained in each model could be determined. Thus, the predictors of level 2 (M8), level 1 (M27), both levels with fixed effects (M35), and both levels with random effects (M36-M91), explained 67.9%, 53.0%, 82.1%, and 81.8%–85.4%, respectively, of the differences observed in the asking price between comarcas.

As we have seen in section 3.2.2, each of the multilevel models had its own purpose and, according to the construction process explained in Fig. 4, the modeling process generated 91 models. All the results of the multilevel models have been summarized in Table 8. The results of the RECA model –M35– are shown in Table 8, as it was similar to the OLS-1 regression model. From the RAMSR model, only the results of those letters (C, E, F, G, and NT) where the interaction with the variables of level 2 (comarca) were significant are shown –M55, M61, M71, M83 y M91–. For the rest of the letters (A and B) the results of the RCRA model are shown –M36 y M44– (Table 8 shows the results in summary form, for the complete results for each individual model, the reader is referred to Table A4.).

With respect to the predictors of level 1 (housing), the results were similar in all models, and as such it is worth noting model 35 (RECA) in

Table 8
Results of the multilevel models for the energy rating characteristic and its interactions. (Complete results of the models are shown in Table A4 of Appendix).

Parameter		Fixed effects		Random effects	
		RECA		RCRA-RAMSR	
		M35		M36-M44-M55-M61-M71-M83-M91	
		B	*SE*	B	*SE*
$\gamma_{0,0}$	Interception	9.704***	0.0502	9.703***	0.051
$\gamma_{1,0}$	*Letter_A*	0.000	0.0157	0.016	0.023
$\gamma_{2,0}$	*Letter_B*	−0.079***	0.0205	−0.011	0.043
$\gamma_{3,0}$	*Letter_C*	0.006	0.0174	0.052	0.040
	Letter_D (ref.)				
$\gamma_{4,0}$	*Letter_E*	−0.097***	0.013	−0.126***	0.020
$\gamma_{5,0}$	*Letter_F*	−0.090***	0.015	−0.110***	0.026
$\gamma_{6,0}$	*Letter_G*	−0.125***	0.013	−0.141***	0.028
$\gamma_{7,0}$	*Letter_NT*	−0.033**	0.012	−0.007	0.023
$\gamma_{8,0}$	*Garden*	0.028***	0.004	0.028***	0.004
$\gamma_{9,0}$	*Apartment*	−0.048***	0.004	−0.047***	0.004
$\gamma_{10,0}$	*Closets*	0.035***	0.003	0.035***	0.003
$\gamma_{11,0}$	*Floor*	0.007***	0.000	0.007***	0.000
$\gamma_{12,0}$	*New_construction*	0.251***	0.013	0.251***	0.013
$\gamma_{13,0}$	*Air_conditioning*	0.082***	0.003	0.082***	0.003
$\gamma_{14,0}$	*State_to_renovate*	−0.179***	0.005	−0.179***	0.005
$\gamma_{15,0}$	*Pool*	0.115***	0.004	0.115***	0.004
$\gamma_{16,0}$	*Parking*	0.124***	0.003	0.124***	0.003
$\gamma_{17,0}$	*Elevator*	0.222***	0.003	0.222***	0.003
$\gamma_{18,0}$	*Bathrooms*	0.230***	0.003	0.230***	0.003
$\gamma_{19,0}$	*Area_m2*	0.006***	0.000	0.006***	0.000
$\gamma_{0,1}$	*Dist_municipality*	−0.005***	0.001	−0.005***	0.001
$\gamma_{0,2}$	*Dist_park*	−0.011***	0.001	−0.011***	0.001
$\gamma_{0,3}$	*Dist_health*	0.012***	0.001	0.012***	0.001
$\gamma_{0,4}$	*Dependency*	0.199***	0.007	0.199***	0.007
$\gamma_{0,5}$	*Dist_school*	0.063***	0.002	0.063***	0.002
$\gamma_{0,6}$	*Gross_income*	0.012***	0.000	0.012***	0.000
$\gamma_{0,7}$	*Coastal_region*	0.291***	0.003	0.291***	0.003
$\gamma_{3,3}$	*Letter_C*Dist_health*			−0.042**	0.014
$\gamma_{4,1}$	*Letter_E*Dist_municipality*			0.011***	0.003
$\gamma_{5,3}$	*Letter_F*Dist_health*			0.022**	0.008
$\gamma_{6,1}$	*Letter_G*Dist_municipality*			0.009*	0.004
$\gamma_{6,3}$	*Letter_G*Dist_health*			0.012*	0.005
$\gamma_{6,4}$	*Letter_G*Dependency*			−0.149***	0.029
$\gamma_{6,5}$	*Letter_G*Dist_school*			0.029***	0.007
$\gamma_{6,7}$	*Letter_G*Coastal_region*			0.063***	0.012
$\gamma_{7,1}$	*Letter_NT*Dist_municipality*			−0.007***	0.002
$\gamma_{7,3}$	*Letter_NT*Dist_health*			−0.011***	0.003
$\gamma_{7,4}$	*Letter_NT*Dependency*			0.056**	0.017
$\gamma_{7,7}$	*Letter_NT*Coastal_region*			−0.030***	0.007
e_{ij}	Residual	0.107***	0.001	0.107***	0.001
u_{0j}	Comarca variance (UN (1,1))	0.021*	0.010	0.021*	0.011
	Covariance means and slopes (UN (2,1))			−0.006	0.004
u_{ij}	Comarca*letter (UN (2,2))			0.002	0.002

NOTES: dependent variable *Ln_Price*; signification: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$; *SE*: Standard Error.

Table 8. Regarding energy ratings, taking the letter D as a reference, the houses with letters A and C had positive and non-significant premiums, while those with the letter B had negative and significant premiums (−7.9%). Housing with low ratings (letters E, F, and G) had negative and significant premiums of −9.7%, −9.0%, and − 12.5%, respectively. It was observed that regarding size, the estimated impact meant that an increase in one square meter of surface area or a bathroom in the residence resulted in an increase in price of 0.6% and 23.0%, respectively. If the property had air conditioning or closets, the impact estimated by the model was 8.2% and 3.5%. If the property was an apartment, a new construction, or required renovation, the impact estimated by the model was −4.8%, 25.1%, and − 17.9% respectively. If the building had an elevator, garage, swimming pool or garden, the impact estimated by the model was 22.2%, 12.4%, 11.5%, and 2.8%, respectively. Regarding the level 2 predictors (comarca), the model estimates that the economic impact of increasing gross income by one thousand euros implies a price increase of 1.2%. Residences that are in coastal towns had a price increase of 29.1%. The results showed that for each kilometer that the residence was further away from a town hall, health center, school or park, the impact estimated by the model was −0.5%, 1.2%, 6.3%, and − 1.1%, respectively. Finally, a one unit increase in the dependency ratio implied an increase in the asking price of 19.9%.

The results regarding the energy rating, after controlling the comarca effect, are shown below. Firstly, when compared to the reference (letter D), the residences with A energy rating (RCRA M36) had an average increase in price of 1.6%, which was not significant enough to be a main effect and did not have a secondary effect with any of the interactions with the level 2 variables (RAMSR M37-M43).

Secondly, when compared to the reference, the residences with B energy rating (RCRA M44) had a premium of −1.1%, which was not significant enough to be a main effect and did not have a secondary effect with any of the interactions with the level 2 variables (RAMSR M45-M51).

Thirdly, the residences with C energy rating (RAMSR M55) had a premium when compared to the reference of 5.2%, which was not significant enough to be a main effect. However, it was significant as a secondary effect, through its interaction with the distance to a health center ($\Upsilon_{3,3} = -0.042$; $p = 0.002$). In other words, for each kilometer away from health centers, residences with letter C rating, their price decreased by −4.2%.

Fourthly, the residences with E energy rating (RAMSR M61) had a premium when compared to the reference of −12.6%, which was significant enough to be a main effect and a secondary effect, through its interaction with the distance to a town hall ($\Upsilon_{4,1} = 0.011$; $p = 0.001$). In other words, for each kilometer away from a town hall, residences with E energy rating, their price increased by 1.1%.

Fifthly, when compared to the reference, the residences with F energy rating (RAMSR M71) had a premium of −11.0%, which was significant enough to be a main effect and a secondary effect, through its interaction with the distance to a health center ($\Upsilon_{5,3} = 0.022$; $p = 0.004$). In other words, for each kilometer away from health centers, residences with F energy rating, their price increased by 2.2%.

Sixthly, the residences with G energy rating (RAMSR M83) had a premium when compared to the reference of −14.1%, which was significant enough to be a main effect and a secondary effects, through its interaction with the distance to a town hall ($\Upsilon_{6,1} = 0.009$; $p = 0.038$), the distance to a health center ($\Upsilon_{6,3} = 0.012$; $p = 0.017$), the dependency ratio ($\Upsilon_{6,4} = -0.149$; $p = 0.000$), distance to the school ($\Upsilon_{6,5} = 0.029$; $p = 0.000$), and if the residence was located in a coastal town ($\Upsilon_{6,7} = 0.063$; $p = 0.000$). In other words, for each kilometer away from a town hall, health center, and school, the price for the residences with G energy rating increased by 0.9%, 1.2%, and 2.9%, respectively. A one-unit increase in the dependency ratio resulted in a decrease in the asking price of −14.9%. Moreover, when the residence was located in a coastal location, the price increased by 6.3%.

Finally, residences that did not publish their energy rating –*Letter_NT*– (RAMSR M91) had a premium when compared to the reference of −0.7%, which was not significant enough to be a main effect. However, it was significant as a secondary effect, through its interaction with the distance to a town hall ($\Upsilon_{7,1} = -0.007$; $p = 0.001$), the distance to a health center ($\Upsilon_{7,3} = -0.011$; $p = 0.000$), the dependency ratio ($\Upsilon_{7,4} = 0.056$; $p = 0.001$), and if the residence was located in a coastal location ($\Upsilon_{7,7} = -0.030$; $p = 0.000$). In other words, for each kilometer away from a town hall and health center, the price for the residences that did not publish their energy rating (*Letter_NT*) decreased −0.7% and − 1.1%, respectively. A one-unit increase in the dependency ratio resulted in an increase in the asking price of 5.6%. However, when the residence was located in a coastal location, the price decreased by −3.0%.

5. Discussion

Regarding the results obtained in the model estimations without interactions (OLS-1 and RECA, Fig. 6a and b), similar effects were obtained in terms of magnitude, direction, and statistical significance, both in the energy rating and location variables. However, when comparing the results of the models without interactions (OLS-1 and RECA) and with interactions (OLS-2 and RCRA+RAMSR, Fig. 6c and d), differences were observed in the magnitude of the parameters accompanying the energy rating variables (letters A, B, C, and NT) and their statistical significance.

In relation to the two models with interactions, the results showed a similar trend in the direction and magnitude of the estimated parameters. This was the case for both the energy rating and location variables and the interactions between the two. However, this was not the case for the interactions between the unrated dwellings (*Letter_NT*) and the location variables (distance to town halls, dependency ratio or coastal town). Behind this result could be the non-significance of these interactions in the estimation of the OLS-2 model.

The multilevel models show that, once the differences due to the comarca had been eliminated, the energy rating label itself had an effect on the asking price (main effect) and also that there was an effect for the relationship of the energy rating with the location characteristics (secondary effects or interactions). This result is in line with the first hypothesis (H_1) and, as such, allows for its acceptance, since it has been shown that the location characteristics influenced the price premiums that generated the energy ratings.

These results are in line with those obtained in other works. Yoshida and Sugiura (2010) suggest that sellers try to mitigate the negative factors that may come with a location (buildings in industrial areas) or a developer's reputation (when they lack financial solvency) by offering residences with a particular (green building) rating in order to attract clients. Although the sellers' strategy is to mitigate the negative location factors by advertising residences with high energy ratings, the rational behavior of the buyer leads them to consider all the characteristics of a residence, and not only the energy rating characteristic. As a consequence, the results offered by the models were that there was a predominance of negative characteristics, which led to discounts in the transaction prices of residences with these qualities. Warren-Myers (2012) notes that valuers appreciate sustainability, however, it must also be kept in mind that this is not the only characteristic to consider, and, if other issues are not evaluated, misleading evaluations may be carried out.

The residences that did not publish their rating (*Letter_NT*) in fact had an energy rating somewhere between A and G, even though the seller did not advertise it. The results for this type of residence show an opposite trend to that of residences with low ratings (letters E, F, and G). This is possibly due to the heterogeneity of energy ratings within this grouping. Moreover, it was observed that the residences advertised without their energy rating (*Letter_NT*) had no statistical difference in terms of price when compared to those residences with the letter D. As such, it can be said that some property sellers have no interest in advertising a property's energy rating, as this allows them to set a higher asking price than the usual amount expected of those residences with the worst ratings (E, F, or G), which is in line with the results of other studies (Cespedes-Lopez et al., 2020; Marmolejo Duarte, 2016; Marmolejo Duarte and Chen, 2019).

With respect to hypothesis 2 (H_2), in which we looked to contrast whether the energy rating conditioned the asking price for housing in the province of Alicante at the comarca level, the RCRA models (M36, M44, M52, M60, M68, M76, and M84), where the predictor of each energy rating (A, B, C, E, F, G, and NT) was taken as the random coefficient, showed that the variance of the slopes (u_{ij}) for each of the letters was not statistically significant. Therefore, the slopes of the regression equations were the same for all comarcas. In other words, the variables that defined the energy ratings were not those responsible for the differences between the average asking prices of the residences in the comarcas.

Lastly, and with regard to the importance of the characteristics to be considered in the analysis, the models estimated that for the province of Alicante, the level 2 predictors (comarca) had a greater impact on the asking prices than those of level 1 (housing). If we observe the variance explained by the level 2 predictors, there is a percentage of 67.9%, while with the level 1 predictors the value obtained is 53.0%. These results are in line with those obtained in other works in which it has been shown that not only do location characteristics considerably increase the explicative power of the model but also that not including them may have a negative impact (Bourassa et al., 2003; Kiel and Zabel, 2008; Waddell et al., 1993; Wen and Tao, 2015).

It should be noted that these results refer to a certain place (province of Alicante) and specific time period (2017–2018), in addition to the fact that the asking prices do not necessarily reflect the transaction prices.

6. Conclusions and policy implications

In this study, the effects of housing location on energy ratings in the province of Alicante were studied. Information from the real estate portal idealista.com, from the period between July 2017 and April 2018,

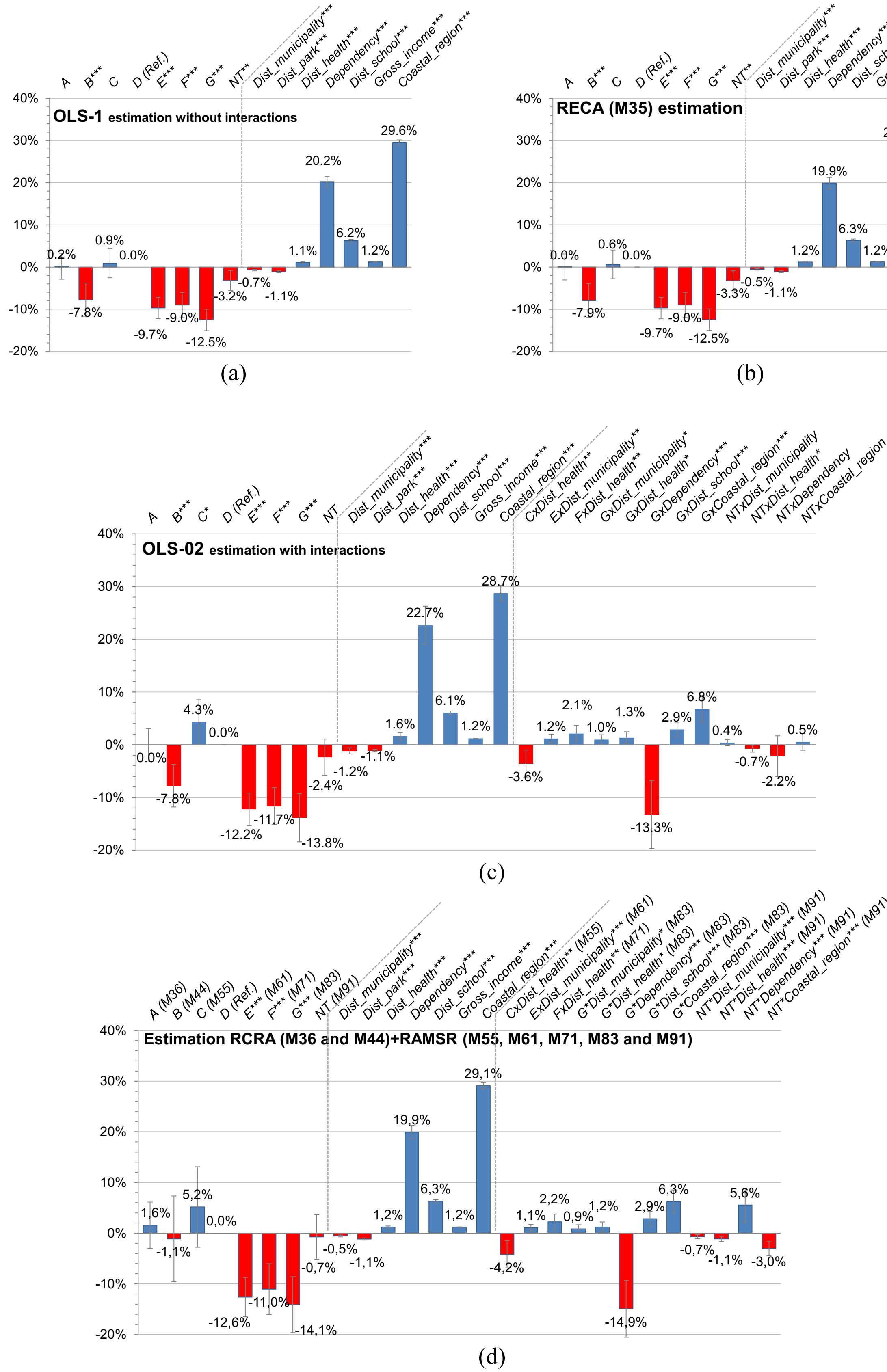


Fig. 6. Frequency graphs with the premium percentages of the asking price of the residences and the CI (95%) according to the energy rating letter with respect to the reference letter (letter D) and the OLS-1, OLS-2, RECA, and RCRA+RAMSR models. Signification: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

was collected. With this information a dataset with 70,170 observations was created. Moreover, 40 variables, which were used to estimate a regression model using OLS with and without interactions and a multilevel model were also generated.

As far as we are aware, this study is the first of its kind to use a multilevel model to analyze how location has an influence on energy ratings and the economic effect that both may have on the asking price. The use of this technique is appropriate given the hierarchical structure of the data and how it allows for more precise estimations regarding standard errors to be made.

The first hypothesis (H_1) estimated that housing location characteristics influenced the price premiums generated by energy ratings. To contrast the hypothesis in an empirical way, both a regression model using OLS, as well as a multilevel model using REML, were employed. The results of both models show that location influences the economic price premium. The results of the regression model show that the residences with high ratings (letters A and C) have non-significant positive premiums. In contrast, the results from the multilevel model show these residences (letters A and C) have a non-significant positive premium as a main effect, and with letter C rating it was observed as a secondary effect that the location had significant negative effects. This is contrary to what can be seen with the residences with low ratings (letters E, F, and G), where the interactions with the location variables had positive effects on the rating.

The second hypothesis (H_2) was to determine whether the energy rating conditioned the asking price for housing in the province of Alicante at a comarca level. To test this hypothesis, this paper uses a multilevel model by REML, since in the OLS regression model the errors may not be independent of each other, and these errors may lead to inefficient or erroneous inference as a consequence of spatial dependence (Dubin, 1998; Pace et al., 1998). The hypothesis is also confirmed as the multilevel models show that energy rating is not a characteristic that determines the difference in the average asking price in the residences in Alicante.

Generally speaking, in this work it has been found that the majority of the variability observed in the prices between the comarcas is a result of location, as indicated in the previous literature.

The results obtained in this paper have relevant policy implications. The introduction of the energy rating in the residential real estate market sector was intended to improve consumer information while promoting the most efficient housing (Ministerio de la Presidencia, 2013; The European Parliament and the Council of the European Union, 2010).

In general, the results of this study highlight that energy efficiency certificates have not been an effective measure (Villca-Pozo and Gonzales-Bustos, 2019) and that currently buyers do not consider that housings with better ratings (letters A, B, or C) bring them savings in energy costs and may even associate higher ratings with high maintenance costs (Yoshida and Sugiura, 2010, 2015; Zheng et al., 2012). Moreover, property sellers do not invest their savings in energy rehabilitation as they do not have the tax incentives to do so, since they are not required to improve the energy rating of their properties in order to put them on sale (García Navarro et al., 2014; Kholodilin et al., 2017; Villca-Pozo and Gonzales-Bustos, 2019). Considering the results, the Spanish State should introduce better tax incentives for rehabilitation such as those carried out in Italy (Bonazzi and Iotti, 2016) or those proposed by Villca-Pozo and Gonzales-Bustos (2019). Moreover, the mechanisms offered by the Public Administration should be reinforced in order to guarantee that users are aware of a property's EPC before purchasing it. Another measure that the Administration should take is making people aware of the need to reduce energy waste in the home and show the level of economic savings that this could bring about (Alberini and Bigano, 2015).

This research shows that the obligation to advertise the energy rating is not widely complied with, as occurs in other studies (Bian and Fabra, 2020; Cornago and Dressler, 2020; Dell'Anna et al., 2019; Marmolejo Duarte and Chen, 2019), so there is little disclosure of the energy rating in the housing offered. This allows sellers who hide the energy rating to publish housing with higher prices, according to better energy ratings (Cespedes-Lopez et al., 2020; Marmolejo Duarte, 2016). Several authors (Bian and Fabra, 2020; Cornago and Dressler, 2020) suggest that greater disclosure of the benefits of more efficient housing would encourage more homeowners to report their energy certificates, which would allow them to differentiate themselves from lower-rated or unrated housing.

In addition, it is observed that the market is not capitalizing on the energy characteristics of housing in real estate offers. This may be mainly due to the lack of information on the implications and advantages of better-rated housing and anomalies in the advertising of energy class. For this reason, governments need to evaluate the effectiveness of their policies, as much stronger measures are needed to overcome the barriers of lack of energy information in real estate offers (Cornago and Dressler, 2020).

Declaration of Competing Interest

Dra. M.F. Céspedes-López, Dr. V.R. Pérez-Sánchez and Dr. R.T. Mora-García, authors of the manuscript "The influence of housing location on energy ratings price premium in Alicante, Spain", declare that they have no conflict of interest.

Data availability

The authors do not have permission to share data.

Acknowledgments

The authors would like to thank the reviewers of the manuscript for their suggestions and recommendations that have improved this document.

The main author would like to thank the "Instituto Alicantino de Cultura Juan Gil-Albert" (https://www.iacjuangilalbert.com/) for the research assistance received for the realization of doctoral theses (2020 call for proposals).

Appendix A

Table A1
Summary of initial OLS-0 regression model results with all variables.

Variables	Non-standardized coefficients	Standardized Coefficients	*t*	*Sig.*	Collinearity statistics	
	B (*SE*)	Beta			Tolerance	*VIF*
Intercepcion	9.820*** (0.016)		607.067	0.000		
Letter_A	0.003 (0.016)	0.001	0.173	0.863	0.424	2.361
Letter_B	−0.080*** (0.020)	−0.010	−3.948	0.000	0.657	1.523
Letter_C	0.004 (0.017)	0.001	0.256	0.798	0.530	1.886
Letter_D (Ref.)						

(*continued on next page*)

Table A1 (*continued*)

Variables	Non-standardized coefficients	Standardized Coefficients	*t*	*Sig.*	Collinearity statistics	
	B (*SE*)	Beta			Tolerance	*VIF*
Letter_E	−0.097*** (0.013)	−0.037	−7.479	0.000	0.161	6.201
Letter_F	−0.088*** (0.015)	−0.018	−5.770	0.000	0.389	2.570
Letter_G	−0.125*** (0.013)	−0.048	−9.659	0.000	0.155	6.434
Letter_NT	−0.032** (0.012)	−0.020	−2.712	0.007	0.072	13.947
Apartment	−0.046*** (0.004)	−0.023	−10.979	0.000	0.883	1.132
Age	0.000 (0.000)	−0.003	−1.182	0.237	0.625	1.600
Area_m2	0.006*** (0.000)	0.312	102.840	0.000	0.419	2.387
Bedrooms	0.004 (0.002)	0.006	1.873	0.061	0.438	2.285
Bathrooms	0.226*** (0.003)	0.205	74.775	0.000	0.514	1.944
Floor	0.007*** (0.000)	0.032	14.731	0.000	0.822	1.216
Closets	0.034*** (0.003)	0.027	12.005	0.000	0.754	1.325
Air_conditioning	0.082*** (0.003)	0.065	29.963	0.000	0.808	1.238
New_construction	0.247*** (0.013)	0.037	18.547	0.000	0.953	1.049
State_to_renovate	−0.180*** (0.005)	−0.070	−34.025	0.000	0.923	1.083
Elevator	0.222*** (0.003)	0.157	68.394	0.000	0.728	1.374
Parking	0.123*** (0.003)	0.095	40.259	0.000	0.694	1.442
Pool	0.106*** (0.004)	0.081	26.964	0.000	0.427	2.341
Garden	0.027*** (0.004)	0.019	7.067	0.000	0.520	1.923
Alicante (Ref.)						
Alcoy	−0.212*** (0.009)	−0.051	−24.500	0.000	0.897	1.115
Alto_vinalopo	−0.078*** (0.015)	−0.010	−5.068	0.000	0.917	1.090
Bajo_segura	−0.061*** (0.005)	−0.037	−12.360	0.000	0.429	2.333
Bajo_vinalopo	0.053*** (0.004)	0.028	12.575	0.000	0.753	1.328
Condado	−0.098*** (0.021)	−0.009	−4.625	0.000	0.973	1.028
Marina_alta	0.136*** (0.005)	0.069	27.018	0.000	0.590	1.694
Marina_baja	0.216*** (0.005)	0.113	43.441	0.000	0.573	1.745
Medio_vinalopo	−0.201*** (0.008)	−0.055	−25.908	0.000	0.848	1.179
Coastal_region	0.262*** (0.003)	0.203	79.766	0.000	0.594	1.682
University	0.007*** (0.000)	0.109	33.264	0.000	0.359	2.784
Dependency	0.217*** (0.007)	0.068	31.920	0.000	0.861	1.162
Gross_income	0.007*** (0.000)	0.116	35.334	0.000	0.357	2.800
FAR	−0.017*** (0.002)	−0.024	−9.612	0.000	0.597	1.674
Dist_park	−0.013*** (0.001)	−0.027	−11.031	0.000	0.663	1.508
Dist_health	0.011*** (0.001)	0.025	10.252	0.000	0.665	1.505
Dist_school	0.052*** (0.002)	0.083	30.440	0.000	0.516	1.938
Dist_municipality	−0.007*** (0.001)	−0.019	−6.803	0.000	0.482	2.076
N	70,170					
R^2	0.730					
R^2 adjusted	0.729					
SE of the estimation	0.324					
F	4980.778					
p	0.000					
Durbin-Watson	1.855					

NOTES: dependent variable *Ln_price*; signification: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$; *SE*: Standard Error; VIF: Variance inflation factor.

Table A2
Complete results of the OLS-1 regression model.

Coefficient	Variable	Non-standardized coefficients		Standardized Coefficients	*t*	*Sig.*	Collinearity statistics	
		B	*SE*	Beta			Tolerance	*VIF*
β_0	Interception	9.762***	0.015		637.319	0.000		
β_1	*Letter_A*	0.002	0.016	0.000	0.111	0.912	0.424	2.361
β_2	*Letter_B*	−0.078***	0.020	−0.009	−3.813	0.000	0.657	1.523
β_3	*Letter_C*	0.009	0.017	0.001	0.499	0.618	0.530	1.886
$\beta_{Ref.letra}$	*Letter_D (Ref.)*							
β_4	*Letter_E*	−0.097***	0.013	−0.037	−7.458	0.000	0.161	6.200
β_5	*Letter_F*	−0.090***	0.015	−0.019	−5.901	0.000	0.389	2.569
β_6	*Letter_G*	−0.125***	0.013	−0.048	−9.589	0.000	0.155	6.433
β_7	*Letter_NT*	−0.032**	0.012	−0.020	−2.653	0.008	0.072	13.942
β_8	*Apartment*	−0.047***	0.004	−0.023	−11.322	0.000	0.924	1.082
β_9	*Area_m2*	0.006***	0.000	0.316	119.604	0.000	0.562	1.780
β_{10}	*Bathrooms*	0.229***	0.003	0.207	77.314	0.000	0.546	1.831
β_{11}	*Floor*	0.007***	0.000	0.033	14.920	0.000	0.825	1.212
β_{12}	*Closets*	0.036***	0.003	0.028	12.445	0.000	0.755	1.325
β_{13}	*Air_conditioning*	0.083***	0.003	0.066	29.842	0.000	0.812	1.231
β_{14}	*New_construction*	0.250***	0.013	0.038	18.619	0.000	0.955	1.047
β_{15}	*State_to_renovate*	−0.177***	0.005	−0.068	−33.309	0.000	0.929	1.076
β_{16}	*Elevator*	0.223***	0.003	0.159	69.130	0.000	0.743	1.345
β_{17}	*Parking*	0.121***	0.003	0.093	39.369	0.000	0.698	1.432
β_{18}	*Pool*	0.111***	0.004	0.085	28.867	0.000	0.447	2.236
β_{19}	*Garden*	0.026***	0.004	0.019	6.810	0.000	0.520	1.923

(*continued on next page*)

Table A2 (*continued*)

Coefficient	Variable	Non-standardized coefficients		Standardized Coefficients	*t*	*Sig.*	Collinearity statistics	
		B	*SE*	Beta			Tolerance	*VIF*
$\beta_{Ref.Comarca}$	*Alicante (ref.)*							
β_{20}	*Alcoy*	−0.228***	0.009	−0.054	−26.147	0.000	0.902	1.108
β_{21}	*Alto_Vinalopo*	−0.112***	0.015	−0.015	−7.217	0.000	0.922	1.085
β_{22}	*Bajo_Segura*	−0.064***	0.005	−0.039	−13.653	0.000	0.479	2.087
β_{23}	*Bajo_Vinalopo*	0.043***	0.004	0.023	10.181	0.000	0.767	1.303
β_{24}	*Condado*	−0.113***	0.021	−0.011	−5.311	0.000	0.976	1.025
β_{25}	*Marina_Alta*	0.123***	0.005	0.062	24.597	0.000	0.608	1.645
β_{26}	*Marina_Baja*	0.187***	0.005	0.098	38.648	0.000	0.611	1.637
β_{27}	*Medio_Vinalopo*	−0.217***	0.008	−0.060	−27.766	0.000	0.851	1.175
β_{28}	*Coastal_region*	0.296***	0.003	0.230	94.652	0.000	0.666	1.502
β_{29}	*Dependency*	0.202***	0.007	0.063	29.699	0.000	0.878	1.139
β_{30}	*Gross_income*	0.012***	0.000	0.189	77.608	0.000	0.657	1.522
β_{31}	*FAR*	−0.013***	0.002	−0.018	−7.149	0.000	0.606	1.649
β_{32}	*Dist_park*	−0.011***	0.001	−0.024	−9.834	0.000	0.666	1.501
β_{33}	*Dist_health*	0.011***	0.001	0.024	9.929	0.000	0.665	1.503
β_{34}	*Dist_school*	0.062***	0.002	0.100	36.875	0.000	0.536	1.867
β_{35}	*Dist_municipality*	−0.007***	0.001	−0.020	−7.207	0.000	0.495	2.021
	N	70,170						
	R^2	0.725						
	Adjusted R^2	0.725						
	SE of the estimation	0.327						
	F	5292.561						
	p	0.000						
	Durbin-Watson	1.854						

NOTES: dependent variable *Ln_price*; signification: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$; *SE*: Standard error; *VIF*: Variance inflation factor.

Table A3
Comparison of the null model with the rest of multilevel models.

Designation	Variables	−2LL	Difference (−2LL)	*t* (*p*)	Comarca variance (u_{0j})		Residual variance (e_{ij})	ICC	Variance explained
					Wald Z (*p*)	Estimate			
				STEP 1: Null Model (without variables)					
M0		122,351.459		125.712 (0.000)	1.995 (0.046)	0.116	0.334	0.257	
				STEP 2a: RMR, with level 2 predictor variables					
M1	*FAR*	121,391.224	960.235	−31.259 (0.000)	1.997 (0.046)	0.108	0.330	0.247	0.063
M2	M1 + *Dist_municipality*	120,567.849	823.375	28.977 (0.000)	1.997 (0.046)	0.096	0.326	0.227	0.172
M3	M2 + *Dist_park*	120,505.440	62.409	−8.549 (0.000)	1.997 (0.046)	0.095	0.326	0.226	0.178
M4	M3 + *Dist_health*	120,056.793	448.647	21.468 (0.000)	1.997 (0.046)	0.093	0.324	0.224	0.193
M5	M4 + *Dependency*	119,692.664	364.129	19.293 (0.000)	1.997 (0.046)	0.094	0.322	0.226	0.188
M6	M5 + *Dist_school*	118,883.009	809.655	28.711 (0.000)	1.997 (0.046)	0.090	0.318	0.221	0.222
M7	M6 + *Gross_income*	104,997.649	13,885.360	123.987 (0.000)	1.997 (0.046)	0.088	0.261	0.251	0.244
M8	M7 + *Coastal_region*	100,523.036	4474.613	68.069 (0.000)	1.993 (0.046)	0.037	0.245	0.132	0.679
				STEP 2b: RMR, with level 1 predictor variables					
M9	*Letter_A*	122,262.924	88.535	9.736 (0.000)	1.997 (0.046)	0.117	0.334	0.259	0.000
M10	M9 + *Letter_B*	122,250.205	12.719	4.236 (0.000)	1.997 (0.046)	0.117	0.334	0.259	0.000
M11	M10 + *Letter_C*	122,090.89	159.315	12.856 (0.000)	1.997 (0.046)	0.116	0.333	0.259	0.000
M12	M11 + *Letter_E*	121,844.648	246.242	−15.945 (0.000)	1.997 (0.046)	0.115	0.332	0.258	0.004
M13	M12 + *Letter_F*	121,619.06	225.588	−15.241 (0.000)	1.997 (0.046)	0.114	0.331	0.256	0.017
M14	M13 + *Letter_G*	119,155.197	2463.863	−50.154 (0.000)	1.997 (0.046)	0.103	0.319	0.244	0.110
M15	M14 + *Letter_NT*	119,128.887	26.31	−5.677 (0.000)	1.997 (0.046)	0.103	0.319	0.244	0.109
M16	M15 + *Garden*	113,889.964	5238.923	73.819 (0.000)		0.072	0.296	0.194	0.382

(*continued on next page*)

Table A3 (*continued*)

Designation	Variables	−2LL	Difference (−2LL)	*t* (*p*)	Comarca variance (u_{0j}) Wald Z (*p*)	Estimate	Residual variance (e_{ij})	ICC	Variance explained
					1.996 (0.046)				
M17	M16 + *Floor*	112,542.496	1347.468	−36.998 (0.000)	1.996 (0.046)	0.071	0.291	0.196	0.387
M18	M17 + *Closets*	109,003.952	3538.544	60.322 (0.000)	1.996 (0.046)	0.062	0.276	0.184	0.462
M19	M18 + *Apartment*	107,759.671	1244.281	35.612 (0.000)	1.995 (0.046)	0.058	0.271	0.176	0.501
M20	M19 + *New_construction*	107,047.523	712.148	26.865 (0.000)	1.995 (0.046)	0.056	0.269	0.174	0.513
M21	M20 + *Air conditioning*	104,239.11	2808.413	53.618 (0.000)	1.995 (0.046)	0.051	0.258	0.165	0.561
M22	M21 + *State_to_renovate*	103,403.516	835.594	−29.128 (0.000)	1.995 (0.046)	0.050	0.255	0.163	0.572
M23	M22 + *Pool*	102,022.547	1380.969	37.463 (0.000)	1.995 (0.046)	0.043	0.250	0.146	0.631
M24	M23 + *Parking*	98,131.239	3891.308	63.331 (0.000)	1.995 (0.046)	0.044	0.236	0.156	0.623
M25	M24 + *Elevator*	91,464.094	6667.145	83.690 (0.000)	1.994 (0.046)	0.038	0.215	0.151	0.670
M26	M25 + *Bathrooms*	72,441.639	19,022.455	147.867 (0.000)	1.996 (0.046)	0.044	0.164	0.211	0.620
M27	M26 + *Area_m2*	61,322.99	11,118.649	109.861 (0.000)	1.997 (0.046)	0.054	0.140	0.280	0.530
	STEP 3: RECA, with level 1 and 2 predictor variables								
M28	M27 + *FAR*	61,329.905	−6.915	−1.960 (0.000)	1.997 (0.046)	0.054	0.140	0.280	0.530
M29	M28 + *Dist_municipality*	60,975.521	347.469	18.987 (0.000)	1.997 (0.046)	0.052	0.139	0.274	0.547
M30	M29 + *Dist_park*	60,906.351	69.17	−8.983 (0.000)	1.997 (0.046)	0.052	0.139	0.274	0.548
M31	M30 + *Dist_health*	60,337.473	568.878	24.143 (0.000)	1.997 (0.046)	0.051	0.138	0.269	0.562
M32	M31 + *Dependency*	58,920.204	1417.269	37.945 (0.000)	1.997 (0.046)	0.050	0.135	0.271	0.566
M33	M32 + *Dist_school*	57,593.952	1326.252	36.739 (0.000)	1.997 (0.046)	0.049	0.133	0.268	0.580
M34	M33 + *Gross_income*	51,135.369	6458.583	82.355 (0.000)	1.997 (0.046)	0.053	0.121	0.306	0.539
M35	M34 + *Coastal_region*	42,620.138	8515.231	95.229 (0.000)	1.994 (0.046)	0.021	0.107	0.162	0.821
	STEP 4: RCRA, with level 1 and 2 predictor variables taking energy ratings as a random coefficient (letters A, B, C, E, F, G, and NT).								
	STEP 4a: Random coefficient of the letter A								
M36	M35	42,609.111	11.027		1.994 (0.046)	0.021	0.107	0.164	0.818
	STEP 4b: Random coefficient of the letter B								
M44	M35	42,591.378	28.760		1.994 (0.046)	0.021	0.107	0.163	0.820
	STEP 4c: Random coefficient of the letter C								
M52	M35	42,600.191	19.947		1.994 (0.046)	0.021	0.107	0.163	0.820
	STEP 4d: Random coefficient of the letter E								
M60	M35	42,590.217	29.921		1.994 (0.046)	0.021	0.107	0.162	0.821
	STEP 4e: Random coefficient of the letter F								
M68	M35	42,604.890	15.248		1.994 (0.046)	0.021	0.107	0.163	0.820
	STEP 4f: Random coefficient of the letter G								
M76	M35	42,520.915	99.223		1.994 (0.046)	0.019	0.107	0.154	0.832
	STEP 4g: Random coefficient of the letter NT								

(*continued on next page*)

Table A3 (*continued*)

Designation	Variables	−2LL	Difference (−2LL)	*t* (*p*)	Comarca variance (u_{0j}) Wald Z (*p*)	Comarca variance (u_{0j}) Estimate	Residual variance (e_{ij})	ICC	Variance explained
M84	M35	42,460.013	160.125		1.976 (0.048)	0.020	0.107	0.158	0.827
STEP 5: RAMSR, with level 1 predictor variables, level 2 predictor variables and the interactions of the energy ratings (letters A, B, C, E, F, G, and NT) with the level 2 variables, taking each letter as a random coefficient.									
STEP 5a: RAMSR, interaction of the letter A with the level 2 variables, taking the letter A as the random coefficient.									
M37	M36 + *Letter_A*Dist_municipality*	42,617.643	−8.532	−0.380 (0.001)	1.994 (0.046)	0.021	0.107	0.164	0.818
M38	M36 + *Letter_A*Dist_park*	42,617.303	−8.192	0.231 (0.001)	1.994 (0.046)	0.021	0.107	0.164	0.818
M39	M36 + *Letter_A*Dist_health*	42,613.146	−4.035	−2.178 (0.000)	1.994 (0.046)	0.021	0.107	0.164	0.818
M40	M36 + *Letter_A*Dependency*	42,612.946	−3.835	0.370 (0.001)	1.994 (0.046)	0.021	0.107	0.164	0.818
M41	M36 + *Letter_A*Dist_school*	42,614.543	−5.432	−1.530 (0.000)	1.994 (0.046)	0.021	0.107	0.164	0.819
M42	M36 + *Letter_A*Gross_income*	42,619.779	−10.668	1.048 (0.000)	1.994 (0.046)	0.021	0.107	0.164	0.818
M43	M36 + *Letter_A*Coastal_region*	42,611.448	−2.337	−2.025 (0.000)	1.994 (0.046)	0.021	0.107	0.164	0.819
STEP 5b: RAMSR, interaction of the letter B with the level 2 variables, taking the letter B as the random coefficient.									
M45	M44 + *Letter_B*Dist_municipality*	42,598.406	−7.028	−0.661 (0.001)	1.994 (0.046)	0.021	0.107	0.163	0.820
M46	M44 + *Letter_B*Dist_park*	42,598.383	−7.005	0.054 (0.001)	1.994 (0.046)	0.021	0.107	0.163	0.820
M47	M44 + *Letter_B*Dist_health*	42,598.089	−6.711	0.427 (0.001)	1.994 (0.046)	0.021	0.107	0.163	0.820
M48	M44 + *Letter_B*Dependency*	42,592.308	−0.930	1.410 (0.000)	1.994 (0.046)	0.021	0.107	0.163	0.820
M49	M44 + *Letter_B*Dist_school*	42,596.694	−5.316	0.978 (0.000)	1.994 (0.046)	0.021	0.107	0.163	0.820
M50	M44 + *Letter_B*Gross_income*	42,601.648	−10.270	−0.561 (0.001)	1.994 (0.046)	0.021	0.107	0.163	0.820
M51	M44 + *Letter_B*Coastal_region*	42,593.970	−2.592	1.602 (0.000)	1.994 (0.046)	0.021	0.107	0.163	0.819
STEP 5c: RAMSR, interaction of the letter C with the level 2 variables, taking the letter C as the random coefficient.									
M53	M52 + *Letter_C*Dist_municipality*	42,607.174	−6.983	−0.958 (0.000)	1.994 (0.046)	0.021	0.107	0.163	0.820
M54	M52 + *Letter_C*Dist_park*	42,606.983	−6.792	0.208 (0.001)	1.994 (0.046)	0.021	0.107	0.163	0.820
M55	M52 + *Letter_C*Dist_health*	42,597.766	2.425	−3.058 (0.000)	1.994 (0.046)	0.021	0.107	0.163	0.820
M56	M55 + *Letter_C*Dependency*	42,600.342	−2.576	−1.101 (0.000)	1.994 (0.046)	0.021	0.107	0.163	0.820
M57	M55 + *Letter_C*Dist_school*	42,603.828	−6.062	0.689 (0.000)	1.994 (0.046)	0.021	0.107	0.163	0.820
M58	M55 + *Letter_C*Gross_income*	42,599.936	−2.170	−3.034 (0.000)	1.994 (0.046)	0.021	0.107	0.163	0.820
M59	M55 + *Letter_C*Coastal_region*	42,602.896	−5.130	0.140 (0.001)	1.994 (0.046)	0.021	0.107	0.163	0.820
STEP 5d: RAMSR, interaction of the letter E with the level 2 variables, taking the letter E as the random coefficient.									
M61	M60 + *Letter_E*Dist_municipality*	42,588.235	1.982	3.443 (0.000)	1.994 (0.046)	0.021	0.107	0.163	0.820
M62	M61 + *Letter_E*Dist_park*	42,597.256	−7.039	−0.232 (0.001)	1.994 (0.046)	0.021	0.107	0.163	0.820
M63	M61 + *Letter_E*Dist_health*	42,589.857	−1.622	2.708 (0.000)	1.994 (0.046)	0.021	0.107	0.163	0.820
M64	M61 + *Letter_E*Dependency*	42,593.639	−5.404	−0.042 (0.001)	1.994 (0.046)	0.021	0.107	0.163	0.820
M65	M61 + *Letter_E*Dist_school*	42,596.142	−7.907	0.534 (0.001)	1.994 (0.046)	0.021	0.107	0.163	0.820
M66	M61 + *Letter_E*Gross_income*	42,600.566	−3.310	0.794 (0.000)	1.994 (0.046)	0.021	0.107	0.163	0.820
M67	M61 + *Letter_E*Coastal_region*	42,593.525	−5.290	1.380 (0.000)	1.994 (0.046)	0.021	0.107	0.164	0.819
STEP 5e: RAMSR, interaction of the letter F with the level 2 variables, taking the letter F as the random coefficient.									

(*continued on next page*)

Table A3 (*continued*)

Designation	Variables	−2LL	Difference (−2LL)	*t* (*p*)	Comarca variance (u_{0j}) Wald Z (*p*)	Comarca variance (u_{0j}) Estimate	Residual variance (e_{ij})	ICC	Variance explained
M69	M68 + *Letter_F*Dist_municipality*	42,611.026	−6.136	1.552 (0.000)	1.994 (0.046)	0.021	0.107	0.163	0.819
M70	M68 + *Letter_F*Dist_park*	42,612.235	−7.345	0.910 (0.000)	1.994 (0.046)	0.021	0.107	0.163	0.819
M71	M68 + *Letter_F*Dist_health*	42,604.654	0.236	2.869 (0.000)	1.994 (0.046)	0.021	0.107	0.163	0.819
M72	M71 + *Letter_F*Dependency*	42,608.646	−3.992	−0.477 (0.001)	1.994 (0.046)	0.021	0.107	0.163	0.819
M73	M71 + *Letter_F*Dist_school*	42,611.709	−7.055	0.147 (0.001)	1.994 (0.046)	0.021	0.107	0.163	0.819
M74	M71 + *Letter_F*Gross_income*	42,615.425	−10.771	−0.990 (0.000)	1.994 (0.046)	0.021	0.107	0.163	0.819
M75	M71 + *Letter_F*Coastal_region*	42,610.238	−5.348	0.667 (0.001)	1.994 (0.046)	0.021	0.107	0.164	0.819
STEP 5f: RAMSR, interaction of the letter G with the level 2 variables, taking the letter G as the random coefficient.									
M77	M76 + *Letter_G*Dist_municipality*	42,493.687	27.228	6.075 (0.000)	1.994 (0.046)	0.020	0.107	0.155	0.831
M78	M77 + *Letter_G*Dist_park*	42,501.339	−7.652	1.365 (0.000)	1.994 (0.046)	0.020	0.107	0.155	0.831
M79	M77 + *Letter_G*Dist_health*	42,485.997	7.690	4.070 (0.000)	1.994 (0.046)	0.020	0.107	0.155	0.830
M80	M79 + *Letter_G*Dependency*	42,472.958	13.039	−4.286 (0.000)	1.994 (0.046)	0.020	0.107	0.155	0.830
M81	M80 + *Letter_G*Dist_school*	42,464.740	8.218	4.023 (0.000)	1.994 (0.046)	0.020	0.107	0.156	0.830
M82	M81 + *Letter_G*Gross_income*	42,470.484	−5.744	2.649 (0.000)	1.994 (0.046)	0.020	0.107	0.156	0.830
M83	M81 + *Letter_G*Coastal_region*	42,443.549	21.191	5.371 (0.000)	1.994 (0.046)	0.020	0.107	0.158	0.827
STEP 5g: RAMSR, interaction of the letter NT with the level 2 variables, taking the letter NT as the random coefficient.									
M85	M84 + *Letter_NT*Dist_municipality*	42,445.095	14.918	−5.068 (0.000)	1.974 (0.048)	0.019	0.107	0.150	0.838
M86	M85 + *Letter_NT*Dist_park*	42,453.870	−8.775	−1.165 (0.000)	1.974 (0.048)	0.019	0.107	0.149	0.838
M87	M85 + *Letter_NT*Dist_health*	42,440.196	4.899	−3.849 (0.000)	1.975 (0.048)	0.019	0.107	0.149	0.839
M88	M87 + *Letter_NT*Dependency*	42,438.170	2.026	2.889 (0.000)	1.974 (0.048)	0.019	0.107	0.149	0.839
M89	M88 + *Letter_NT*Dist_school*	42,445.202	−7.032	−1.412 (0.000)	1.974 (0.048)	0.019	0.107	0.148	0.840
M90	M88 + *Letter_NT*Gross_income*	42,451.084	−12.914	−0.967 (0.000)	1.974 (0.048)	0.019	0.107	0.149	0.839
M91	M88 + *Letter_NT*Coastal_region*	42,429.714	8.456	−4.089 (0.000)	1.974 (0.048)	0.017	0.107	0.137	0.854

Table A4
Complete results of the multilevel models for the energy rating characteristic and its interactions.

Parameter			Fixed effects	Random effects						
			RECA	RCRA	RCRA	RAMSR	RAMSR	RAMSR	RAMSR	RAMSR
				Letter A	Letter B	Letter C	Letter E	Letter F	Letter G	Letter NT
			M35	M36	M44	M55	M61	M71	M83	M91
$\Upsilon_{0,0}$	Interception	Est.	9.704***	9.703***	9.704***	9.704***	9.706***	9.704***	9.708***	9.686***
		(*SE*)	(0.050)	(0.051)	(0.050)	(0.050)	(0.050)	(0.050)	(0.050)	(0.047)
		t	193.218	191.889	192.500	192.806	192.841	192.445	196.126	207.480
$\Upsilon_{1,0}$	*Letter_A*	Est.	0.000	**0.016**	0.000	0.000	0.000	0.000	0.000	0.001
		(*SE*)	(0.016)	**(0.023)**	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
		t	0.018	**0.677**	0.015	0.012	0.007	0.022	-0.009	0.032
$\Upsilon_{2,0}$	*Letter_B*	Est.	−0.079***	−0.079***	**−0.011**	−0.079***	−0.080***	−0.079***	−0.080***	−0.074***
		(*SE*)	(0.020)	(0.020)	**(0.043)**	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)
		t	−3.875	−3.883	**−0.258**	−3.874	−3.906	−3.881	−3.895	−3.621
$\Upsilon_{3,0}$	*Letter_C*	Est.	0.006	0.006	0.006	**0.052**	0.006	0.006	0.006	0.007
		(*SE*)	(0.017)	(0.017)	(0.017)	**(0.040)**	(0.017)	(0.017)	(0.017)	(0.017)
		t	0.357	0.359	0.356	**1.281**	0.354	0.353	0.373	0.412

(*continued on next page*)

Table A4 (*continued*)

Parameter			Fixed effects	Random effects						
			RECA	RCRA	RCRA	RAMSR	RAMSR	RAMSR	RAMSR	RAMSR
				Letter A	Letter B	Letter C	Letter E	Letter F	Letter G	Letter NT
			M35	M36	M44	M55	M61	M71	M83	M91
	Letter_D (ref.)									
		Est.	−0.097***	−0.097***	−0.097***	−0.097***	**−0.126*** **	−0.097***	−0.098***	−0.096***
$\Upsilon_{4,0}$	*Letter_E*	(*SE*)	(0.013)	(0.013)	(0.013)	(0.013)	**(0.020)**	(0.013)	(0.013)	(0.013)
		t	−7.460	−7.459	−7.453	−7.453	**−6.358**	−7.455	−7.535	−7.336
		Est.	−0.090***	−0.090***	−0.090***	−0.090***	−0.090***	**−0.110*** **	−0.091***	−0.091***
$\Upsilon_{5,0}$	*Letter_F*	(*SE*)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	**(0.026)**	(0.015)	(0.015)
		t	−5.889	-5.883	-5.880	-5.883	-5.872	**-4.325**	-5.977	−5.964
		Est.	−0.125***	−0.125***	−0.125***	−0.125***	−0.125***	−0.125***	**−0.141*** **	−0.119***
$\Upsilon_{6,0}$	*Letter_G*	(*SE*)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	**(0.028)**	(0.013)
		t	−9.540	-9.539	-9.529	-9.533	-9.537	-9.527	**-4.995**	−9.081
		Est.	−0.033**	−0.033**	−0.033**	−0.033**	−0.033**	−0.033**	−0.033**	**−0.007**
$\Upsilon_{7,0}$	*Letter_NT*	(*SE*)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	**(0.023)**
		t	−2.708	-2.710	-2.711	-2.708	-2.726	-2.712	-2.719	**−0.324**
		Est.	0.028***	0.028***	0.029***	0.029***	0.029***	0.029***	0.029***	0.029***
$\Upsilon_{8,0}$	*Garden*	(*SE*)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
		t	7.356	7.367	7.420	7.426	7.502	7.402	7.524	7.524
		Est.	−0.048***	−0.047***	−0.048***	−0.048***	−0.048***	−0.048***	−0.048***	−0.048***
$\Upsilon_{9,0}$	*Apartment*	(*SE*)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
		t	−11.513	-11.499	-11.521	-11.539	-11.615	-11.556	-11.531	-11.706
		Est.	0.035***	0.035***	0.036***	0.036***	0.036***	0.036***	0.035***	0.037***
$\Upsilon_{10,0}$	*Closets*	(*SE*)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
		t	12.254	12.246	12.303	12.299	12.409	12.303	12.264	12.680
		Est.	0.007***	0.007***	0.007***	0.007***	0.007***	0.007***	0.007***	0.007***
$\Upsilon_{11,0}$	*Floor*	(*SE*)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
		t	14.715	14.732	14.681	14.718	14.655	14.717	14.991	14.756
		Est.	0.251***	0.251***	0.251***	0.247***	0.252***	0.251***	0.252***	0.249***
$\Upsilon_{12,0}$	*New_construction*	(*SE*)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
		t	18.741	18.731	18.682	18.330	18.765	18.728	18.821	18.571
		Est.	0.082***	0.082***	0.082***	0.082***	0.082***	0.082***	0.081***	0.081***
$\Upsilon_{13,0}$	*Air_conditioning*	(*SE*)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
		t	29.562	29.572	29.596	29.509	29.490	29.561	29.513	29.338
		Est.	−0.179***	−0.179***	−0.179***	−0.179***	−0.179***	−0.179***	−0.179***	−0.180***
$\Upsilon_{14,0}$	*State_to_renovate*	(*SE*)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
		t	−33.685	-33.665	-33.680	-33.665	-33.750	-33.713	-33.786	-33.960
		Est.	0.115***	0.115***	0.115***	0.116***	0.115***	0.115***	0.117***	0.115***
$\Upsilon_{15,0}$	*Pool*	(*SE*)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
		t	30.288	30.287	30.250	30.327	30.153	30.203	30.634	30.219
		Est.	0.124***	0.124***	0.124***	0.124***	0.124***	0.124***	0.123***	0.124***
$\Upsilon_{16,0}$	*Parking*	(*SE*)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
		t	40.575	40.565	40.560	40.557	40.618	40.613	40.559	40.642
		Est.	0.222***	0.222***	0.222***	0.222***	0.222***	0.222***	0.220***	0.221***
$\Upsilon_{17,0}$	*Elevator*	(*SE*)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
		t	68.784	68.784	68.807	68.799	68.768	68.807	68.341	68.621
		Est.	0.230***	0.230***	0.229***	0.230***	0.230***	0.230***	0.229***	0.229***
$\Upsilon_{18,0}$	*Bathrooms*	(*SD*)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
		t	77.680	77.625	77.607	77.640	77.699	77.711	77.518	77.643
		Est.	0.006***	0.006***	0.006***	0.006***	0.006***	0.006***	0.006***	0.006***
$\Upsilon_{19,0}$	*Area_m2*	(*SE*)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
		t	119.364	119.409	119.410	119.385	119.372	119.363	119.660	119.378
		Est.	−0.005***	−0.005***	−0.005***	−0.005***	−0.006***	−0.005***	−0.006***	0.000
$\Upsilon_{0,1}$	*Dist_municipality*	(*SE*)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
		t	−5.643	-5.635	-5.637	-5.669	-6.216	-5.705	-6.114	0.056
		Est.	−0.011***	−0.011***	−0.011***	−0.011***	−0.011***	−0.011***	−0.011***	−0.011***
$\Upsilon_{0,2}$	*Dist_park*	(*SE*)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
		t	−9.740	-9.706	-9.778	-9.808	-9.627	-9.669	-9.160	-9.160
		Est.	0.012***	0.012***	0.012***	0.012***	0.012***	0.012***	0.011***	0.022***
$\Upsilon_{0,3}$	*Dist_health*	(*SE*)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)
		t	10.790	10.792	10.810	11.028	10.949	10.453	10.045	8.401
		Est.	0.199***	0.199***	0.199***	0.199***	0.199***	0.199***	0.209***	0.154***
$\Upsilon_{0,4}$	*Dependency*	(*SE*)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.016)
		t	29.393	29.401	29.379	29.391	29.336	29.385	29.959	9.878
		Est.	0.063***	0.063***	0.063***	0.063***	0.063***	0.063***	0.061***	0.063***
$\Upsilon_{0,5}$	*Dist_school*	(*SD*)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
		t	37.381	37.362	37.390	37.344	37.421	37.404	35.390	37.141
		Est.	0.012***	0.012***	0.012***	0.012***	0.012***	0.012***	0.012***	0.012***
$\Upsilon_{0,6}$	*Gross_income*	(*SE*)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
		t	78.395	78.419	78.401	78.368	78.298	78.312	78.144	78.114
$\Upsilon_{0,7}$	*Coastal_region*									

(*continued on next page*)

Table A4 (*continued*)

	Parameter		Fixed effects	Random effects						
			RECA	RCRA	RCRA	RAMSR	RAMSR	RAMSR	RAMSR	RAMSR
				Letter A	Letter B	Letter C	Letter E	Letter F	Letter G	Letter NT
			M35	M36	M44	M55	M61	M71	M83	M91
		Est.	0.291***	0.291***	0.291***	0.291***	0.292***	0.292***	0.288***	0.318***
		(*SE*)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.007)
		t	95.229	95.227	95.311	95.191	95.349	95.295	91.470	47.571
		Est.				**−0.042****				
$\gamma_{3,3}$	*Letter_C*Dist_health*	(*SE*)				**(0.014)**				
		t				**−3.058**				
		Est.					**0.011*****			
$\gamma_{4,1}$	*Letter_E*Dist_municipality*	(*SE*)					**(0.003)**			
		t					**3.443**			
		Est.						**0.022****		
$\gamma_{5,3}$	*Letter_F*Dist_health*	(*SE*)						**(0.008)**		
		t						**2.869**		
		Est.							**0.009***	
$\gamma_{6,1}$	*Letter_G*Dist_municipality*	(*SE*)							**(0.004)**	
		t							**2.076**	
		Est.							**0.012***	
$\gamma_{6,3}$	*Letter_G*Dist_health*	(*SE*)							**(0.005)**	
		t							**2.394**	
		Est.							**−0.149*****	
$\gamma_{6,4}$	*Letter_G*Dependency*	(*SE*)							**(0.029)**	
		t							**−5.221**	
		Est.							**0.029*****	
$\gamma_{6,5}$	*Letter_G*Dist_school*	(*SE*)							**(0.007)**	
		t							**3.838**	
		Est.							**0.063*****	
$\gamma_{6,7}$	*Letter_G*Coastal_region*	(*SE*)							**(0.012)**	
		t							**5.371**	
		Est.								**−0.007*****
$\gamma_{7,1}$	*Letter_NT*Dist_municipality*	(*SE*)								**(0.002)**
		t								**−3.317**
		Est.								**−0.011*****
$\gamma_{7,3}$	*Letter_NT*Dist_health*	(*SE*)								**(0.003)**
		t								**−3.943**
		Est.								**0.056****
$\gamma_{7,4}$	*Letter_NT*Dependency*	(*SE*)								**(0.017)**
		t								**3.247**
		Est.								**−0.030*****
$\gamma_{7,7}$	*Letter_NT*Coastal_region*	(*SE*)								**(0.007)**
		t								**−4.089**
	Covariance parameter estimates									
		Est.	0.107***	0.107***	0.107***	0.107***	0.107***	0.107***	0.107***	0.107***
e_{ij}	Residual	(*SE*)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
		Z	187.263	187.257	187.256	187.254	187.254	187.254	187.247	187.248
	Comarca variance	Est.	0.021*	0.021*	0.021*	0.021*	0.021*	0.021*	0.020*	0.017*
	(UN (1,1))	(*SE*)	(0.010)	(0.011)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.009)
		Z	1.994	1.994	1.994	1.994	1.994	1.994	1.994	1.974
u_{0j}	Covariance means and	Est.		−0.006	−0.015	−0.005	−0.002	−0.006	0.000	0.001
	slopes	(*SE*)		(0.004)	(0.009)	(0.006)	(0.002)	(0.004)	(0.003)	(0.002)
	(UN (2,1))	*Z*		−1.584	−1.765	−0.860	−0.920	−1.494	0.051	0.447
	Comarca*letter	Est.		0.002	0.012	0.007	0.001	0.003	0.003	0.002
u_{ij}	(UN (2,2))	(*SE*)		(0.002)	(0.008)	(0.005)	(0.001)	(0.002)	(0.002)	(0.001)
		Z		1.285	1.546	1.472	1.608	1.326	1.655	1.832

NOTES: dependent variable *Ln_Price*; signification: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$; Est.: Estimation; *SE*: Standard Error; Z: Wald Z.

References

Acevedo Álvarez, R., 2008. Los Modelos Jerárquicos Lineales: Fundamentos Básicos Para su uso y Aplicación. Instituto de Investigaciones Psicológicas, Universidad de Costa Rica, San José.

Addae-Dapaah, K., Chieh, S.J., 2011. Green mark certification: does the market understand? J. Sustain. Real Estate 3 (1), 162–191. https://doi.org/10.1080/10835547.2011.12091828.

Aggarwal, C.C., 2013. Outlier Analysis, 1st ed. 2013. ed. Springer, New York, New York, NY. https://doi.org/10.1007/978-1-4614-6396-2.

Agnew, K., Lyons, R.C., 2018. The impact of employment on housing prices: detailed evidence from FDI in Ireland. Reg. Sci. Urban Econ. 70, 174–189. https://doi.org/10.1016/j.regsciurbeco.2018.01.011.

Alarcón, R., Blanca, M.J., Arnau, J., Bono, R., 2015. Modelado jerárquico por pasos: análisis multinivel del estrés cotidiano en adolescentes. Revista Mexicana de Psicología 32 (2), 124–133.

Alberini, A., Bigano, A., 2015. How effective are energy-efficiency incentive programs? Evidence from Italian homeowners. Energy Econ. 52, S76–S85. https://doi.org/10.1016/j.eneco.2015.08.021.

Allison, P.D., 1977. Testing for interaction in multiple regression. Am. J. Sociol. 83 (1), 144–153.

Allison, P.D., 1998. Multiple Regression: A Primer. Pine Forge Press, California.

Allison, P.D., 2012. When can You Safely Ignore Multicollinearity, pp. 1–2.

Ankamah Yeboah, I., Rehdanz, K., 2014. Explaining the variation in the value of building energy efficiency certificates: a quantitative metaanalysis. In: Kiel Working Paper, 1949, p. 25.

Balluerka Lasa, N., Vergara Iraeta, A.I., Arnau y Gras, J., 2002. Diseños de investigación experimental en psicología : modelos y análisis de datos mediante el SPSS 10.0.

Bauer, T.K., Feuerschütte, S., Kiefer, M., de Meulen, P., Micheli, M., Schmidt, T., Wilke, L.-H., 2013. Ein hedonischer Immobilienpreisindex auf Basis von Internetdaten: 2007–2011. AStA Wirtschafts- und Sozialstatistisches Archiv 7 (1), 5–30. https://doi.org/10.1007/s11943-012-0125-7.
Bian, X., Fabra, N., 2020. Incentives for information provision: energy efficiency in the Spanish rental market. Energy Econ. 90, 104813 https://doi.org/10.1016/j.eneco.2020.104813.
Bonazzi, G., Iotti, M., 2016. Evaluation of investment to improve the quality of buildings and generate positive externalities. Energy Manag. 17 (153), 79–85.
Bonifaci, P., Copiello, S., 2015. Price premium for buildings energy efficiency: empirical findings from a hedonic model. Valori e Valutazioni 14, 5–15.
Bourassa, S.C., Hoesli, M., Peng, V.S., 2003. Do housing submarkets really matter? J. Hous. Econ. 12 (1), 12–28. https://doi.org/10.1016/S1051-1377(03)00003-2.
Brandt, S., Maennig, W., 2012. The impact of rail access on condominium prices in Hamburg. Transportation 39 (5), 997–1017. https://doi.org/10.1007/s11116-011-9379-0.
Brounen, D., Kok, N., 2011. On the economics of energy labels in the housing market. J. Environ. Econ. Manag. 62 (2), 166–179. https://doi.org/10.1016/j.jeem.2010.11.006.
Brown, K.H., Uyar, B., 2004. A hierarchical linear model approach for assessing the effects of house and neighborhood characteristics on housing prices. J. Real Estate Pract. Educ. 7 (1), 15–23.
Brown, M.J., Watkins, T., 2016. The "Green Premium" for Environmentally Certified Homes: A meta-Analysis and Exploration, p. 43. https://doi.org/10.13140/RG.2.1.1468.1368.
Cajias, M., Piazolo, D., 2013. Green performs better: energy efficiency and financial return on buildings. J. Corp. Real Estate 15 (1), 53–72. https://doi.org/10.1108/JCRE-12-2012-0031.
CECD, Consejería de Educación, Cultura y Deporte, 2019. Centros docentes de la Comunidad Valenciana.
Cespedes-Lopez, M.-F., Mora-Garcia, R.-T., Perez-Sanchez, V.R., Perez-Sanchez, J.-C., 2019. Meta-analysis of price premiums in housing with energy performance certificates (EPC). Sustainability 11 (22). https://doi.org/10.3390/su11226303.
Cespedes-Lopez, M.-F., Mora-Garcia, R.-T., Perez-Sanchez, V.R., Marti-Ciriquian, P., 2020. The influence of energy certification on housing sales prices in the province of Alicante (Spain). Appl. Sci. 10 (20), 7129. https://doi.org/10.3390/app10207129.
Chasco Yrigoyen, C., Sánchez Reyes, B., 2012. Externalidades ambientales y precio de la vivienda en Madrid: un análisis con regresión cuantílica espacial. Revista Galega de Economía 21 (2), 1–21.
Chegut, A., Eichholtz, P., Holtermans, R., 2016. Energy efficiency and economic value in affordable housing. Energy Policy 97, 39–49. https://doi.org/10.1016/j.enpol.2016.06.043.
Cichulska, A., Cellmer, R., 2018. Analysis of prices in the housing market using mixed models. Real Estate Manag. Valuat. 26 (4), 102–111. https://doi.org/10.2478/remav-2018-0040.
Copiello, S., Donati, E., 2021. Is investing in energy efficiency worth it? Evidence for substantial price premiums but limited profitability in the housing sector. Energy Build. 251, 111371 https://doi.org/10.1016/j.enbuild.2021.111371.
Cornago, E., Dressler, L., 2020. Incentives to (not) disclose energy performance information in the housing market. Resour. Energy Econ. 61, 101162 https://doi.org/10.1016/j.reseneeco.2020.101162.
de Ayala, A., Galarraga, I., Spadaro, J.V., 2016. The price of energy efficiency in the Spanish housing market. Energy Policy 94 (Supplement C), 16–24. https://doi.org/10.1016/j.enpol.2016.03.032.
De la Cruz, F., 2008. Modelos multinivel. Revista Peruana de Epidemiología 12 (3), 1–8.
Dell'Anna, F., Bravi, M., Marmolejo-Duarte, C., Bottero, M.C., Chen, A., 2019. EPC green premium in two different European climate zones: a comparative study between Barcelona and Turin. Sustainability 11 (20), 5605. https://doi.org/10.3390/su11205605.
Deng, Y., Li, Z., Quigley, J.M., 2012. Economic returns to energy-efficient investments in the housing market: evidence from Singapore. Reg. Sci. Urban Econ. 42 (3), 506–515. https://doi.org/10.1016/j.regsciurbeco.2011.04.004.
Dubin, R.A., 1998. Spatial autocorrelation: a primer. J. Hous. Econ. 7 (4), 304–327. https://doi.org/10.1006/jhec.1998.0236.
Evangelista, R., Ramalho, E.A., Andrade e Silva, J., 2020. On the use of hedonic regression models to measure the effect of energy efficiency on residential property transaction prices: evidence for Portugal and selected data issues. Energy Econ. 86, 104699 https://doi.org/10.1016/j.eneco.2020.104699.
Fizaine, F., Voye, P., Baumont, C., 2018. Does the literature support a high willingness to pay for green label buildings? An answer with treatment of publication bias. Revue D'économie Politique 128 (5), 1013–1046. https://doi.org/10.3917/redp.285.1013.
Fuerst, F., Shimizu, C., 2016. Green luxury goods? The economics of eco-labels in the Japanese housing market. J. Jpn. Int. Econ. 39, 108–122. https://doi.org/10.1016/j.jjie.2016.01.003.
Fuerst, F., McAllister, P., Nanda, A., Wyatt, P., 2013. An Investigation of the Effect of EPC Ratings on House Prices. Department of Energy & Climate Change, p. 41.
Fuerst, F., McAllister, P., Nanda, A., Wyatt, P., 2015. Does energy efficiency matter to home-buyers? An investigation of EPC ratings and transaction prices in England. Energy Econ. 48, 145–156. https://doi.org/10.1016/j.eneco.2014.12.012.
Fuerst, F., McAllister, P., Nanda, A., Wyatt, P., 2016. Energy performance ratings and house prices in Wales: an empirical study. Energy Policy 92 (Supplement C), 20–33. https://doi.org/10.1016/j.enpol.2016.01.024.
García Navarro, J., González Díaz, M.J., Valdivieso, M., 2014. Assessment of construction costs and energy consumption resulting from house energy ratings in a residential building placed in Madrid: "Precost&e study". Inf. Constr. 66 (535), e026 https://doi.org/10.3989/ic.13.052.
Gelman, A., 2006. Multilevel (hierarchical) modeling: what it can and cannot do. Technometrics 48 (3), 432–435. https://doi.org/10.1198/004017005000000661.
Giraldo Osorio, A., Vélez Álvarez, C., 2014. The primary health care from the users perspective. Enfermería Global 13 (2), 232–251. https://doi.org/10.6018/eglobal.13.2.181571.
Heck, R.H., Thomas, S.L., Tabata, L.N., 2012. Multilevel Modeling of Categorical Outcomes Using IBM SPSS. Ringgold Inc, Portland. https://doi.org/10.4324/9780203808986.
Horowitz, J.L., 1992. The role of the list price in housing markets: theory and an econometric model. J. Appl. Econ. 7 (2), 115–129. https://doi.org/10.1002/jae.3950070202.
Hyland, M., Lyons, R.C., Lyons, S., 2013. The value of domestic building energy efficiency - evidence from Ireland. Energy Econ. 40 (Supplement C), 943–952. https://doi.org/10.1016/j.eneco.2013.07.020.
IBM Corp, 2016. IBM SPSS Statistics for Windows, v. 25. Armonk, Nueva York.
IGN, Instituto Geográfico Nacional, 2018. Sistema de Información sobre Ocupación del Suelo de España (SIOSE).
INE, Instituto Nacional de Estadística, 2011. Censo de Población y Viviendas de 2011.
INE, Instituto Nacional de Estadística, 2021. Atlas de distribución de renta de los hogares (2018).
Jayantha, W.M., Wan Sze, M., 2013. Effect of green labelling on residential property price: a case study in Hong Kong. J. Facil. Manag. 11 (1), 31–51. https://doi.org/10.1108/14725961311301457.
Jensen, O.M., Hansen, A.R., Kragh, J., 2016. Market response to the public display of energy performance rating at property sales. Energy Policy 93, 229–235. https://doi.org/10.1016/j.enpol.2016.02.029.
Johnson, R.R., Kuby, P.J., 2011. Elementary Statistics, 11 ed. Cengage Learning, Boston.
Jones, K., Bullen, N., 1994. Contextual models of urban house prices: a comparison of fixed- and random-coefficient models developed by expansion. Econ. Geogr. 70 (3), 252–272. https://doi.org/10.2307/143993.
Kahn, P.H., Kellert, S.R., 2002. Children and Nature: Psychological, Sociocultural, and Evolutionary Investigations. The MIT Press, Cambridge, Massachusetts. https://doi.org/10.7551/mitpress/1807.001.0001.
Kain, J.F., Quigley, J.M., 1975. Housing Markets and Racial Discrimination: A Microeconomic Analysis. National Bureau of Economic Research, New York.
Kaplan, R., Kaplan, S., 1989. The Experience of Nature: A Pshychological Perspective. Cambridge University Press, Cambridge.
Kholodilin, K.A., Mense, A., Michelsen, C., 2017. The market value of energy efficiency in buildings and the mode of tenure. Urban Stud. 54 (14), 3218–3238. https://doi.org/10.1177/0042098016669464.
Kiel, K.A., Zabel, J.E., 2008. Location, location, location: the 3L approach to house price determination. J. Hous. Econ. 17 (2), 175–190. https://doi.org/10.1016/j.jhe.2007.12.002.
Kim, S., Lim, B.T.H., Kim, J., 2017. Green features, symbolic values and rental premium: systematic review and meta-analysis. Procedia Eng. 180, 41–48. https://doi.org/10.1016/j.proeng.2017.04.163.
Knight, J., Sirmans, C.F., Turnbull, G., 1998. List price information in residential appraisal and underwriting. J. Real Estate Res. 15 (1), 59–76. https://doi.org/10.1080/10835547.1998.12090913.
Kweon, B.-S., Sullivan, W.C., Wiley, A.R., 1998. Green common spaces and the social integration of Inner-City older adults. Environ. Behav. 30 (6), 832–858. https://doi.org/10.1177/001391659803000605.
Malpezzi, S., 2003. Hedonic pricing models: A selective and applied review. In: O'Sullivan, T., Gibb, K. (Eds.), Housing Economics and Public Policy. Blackwell Science, Great Britain. https://doi.org/10.1002/9780470690680.ch5.
Mariani, M.C., Tweneboah, O.K., Pia Beccar-Varela, M., 2021. Data Preprocessing and Data Validations, Data Science in Theory and Practice. John Wiley & Sons, Inc, Hoboken (USA), pp. 109–120. https://doi.org/10.1002/9781119674757.ch8.
Marmolejo Duarte, C., 2016. La incidencia de la calificación energética sobre los valores residenciales: un análisis para el mercado plurifamiliar en Barcelona. Inf. Constr. 68 (543), e156 https://doi.org/10.3989/ic.16.053.
Marmolejo Duarte, C., Chen, A., 2019. The impact of EPC rankings on the Spanish residential market: an analysis for Barcelona, valence and Alicante. Ciudad y Territorio. Estudios Territoriales 51 (199), 101–118.
Martínez Garrido, C., Murillo Torrecilla, F.J., 2013. El uso de los Modelos Multinivel en la Investigación Educativa. Estadísticas avanzadas para conocer y cambiar la educación en América Latina. In: Salcedo, A. (Ed.), Estadística en la Investigación: competencia transversal en la formación universitaria. Programa de Cooperación Interfacultades. Universidad Central de Venezuela Caracas, pp. 47–70.
McCord, M., Lo, D., Davis, P.T., Hemphill, L., McCord, J., Haran, M., 2020. A spatial analysis of EPCs in the Belfast metropolitan area housing market. J. Prop. Res. 37 (1), 25–61. https://doi.org/10.1080/09599916.2019.1697345.
Merino Noé, J., 2017. La potencialidad de la Regresión Logística Multinivel. Una propuesta de aplicación en el análisis del estado de salud percibido. EMPIRIA Revista de Metodología de Ciencias Sociales 36, 177–211. https://doi.org/10.5944/empiria.36.2017.17865.
Ministerio de la Presidencia, 2013. Real Decreto 235/2013, de 5 de abril, por el que se aprueba el procedimiento básico para la certificación de la eficiencia energética de los edificios. Boletín Oficial del Estado, Madrid, p. 15.
Ministerio de Sanidad, 2021. Informe Anual del Sistema Nacional de Salud 2019, Informes, estudios e investigación 2021. Ministerio de Sanidad.
MITMA, Ministerio de Transportes, Movilidad y Agenda Urbana, 2020. Transacciones Inmobiliarias (Compraventa).
Montero Granados, R., 2011. Efectos fijos o aleatorios: test de especificación. Documentos de Trabajo en Economía Aplicada. Universidad de Granada, p. 5.

Mora-Garcia, R.-T., 2016. Modelo explicativo de las variables intervinientes en la calidad del entorno construido de las ciudades. Departamento de Edificación y Urbanismo. Universidad de Alicante, p. 464.
Mudgal, S., Lyons, L., Cohen, F., Lyons, R.C., Fedrigo-Fazio, D., 2013. Energy Performance Certificates in Buildings and Their Impact on Transaction Prices and Rents in Selected EU Countries, p. 158.
Murillo Torrecilla, F.J., 2008. Los modelos multinivel como herramienta para la investigación educativa. Magis. Revista Internacional de Investigación Educativa 1 (1), 45–62.
Notaries-France, 2018. La valeur verte des logements en 2017. Étude Statistiques Immobilières, France métropolitaine, p. 11.
Olaussen, J.O., Oust, A., Solstad, J.T., 2017. Energy performance certificates – informing the informed or the indifferent? Energy Policy 111, 246–254. https://doi.org/10.1016/j.enpol.2017.09.029.
Osborne, J.W., 2000. Advantages of hierarchical linear modeling. Pract. Assess. Res. Eval. 7, 1–4. https://doi.org/10.7275/pmgn-zx89.
Pace, R.K., Barry, R., Sirmans, C.F., 1998. Spatial statistics and real estate. J. Real Estate Financ. Econ. 17 (1), 5–13. https://doi.org/10.1023/A:1007783811760.
Pardo, A., Ruiz, M.A., San Martín, R., 2007. Cómo ajustar e interpretar modelos multinivel con SPSS. Psicothema 19 (2), 308–321.
Pérez Fernández, V., 2012. Los modelos multinivel en el análisis de factores de riesgo de sibilancias recurrentes en lactantes. Enfoques frecuentista y bayesianao, Departamento de Cirugía, Pediatría, Ginecología y Obstetricia. Universidad de Murcia, p. 145.
Ramos, A., Pérez Alonso, A., Silva, S., 2015. Valuing energy performance certificates in the Portuguese residential. Working Paper RSCAS 2015, 36.
Raudenbush, S.W., Bryk, A.S., 2002. Hierarchical Linear Models : Applications and Data Analysis Methods, 2nd ed. Sage Publications, Inc, California.
Salkind, N.J., 1999. Métodos de Investigación, 3 ed. Pearson Educación, Méjico.
Salvi, M., Horehájová, A., Müri, R., 2008. Minergie macht sich bezahlt. In: Meins, E. (Ed.), CCRS, Center for Corporate Responsibility and Sustainability. Universität Zürich, p. 11.
SEG, Sede Electrónica del Catastro, 2019. Información alfanumérica y cartografía vectorial.
Shimizu, C., 2010. Will Green Buildings Be Appropriately Valued by the Market? Reitaku Institute of Political Economics and Social Studies. Reitaku University, Kashiwa, p. 30.
Shimizu, C., Nishimura, K.G., Watanabe, T., 2012. House prices from magazines, realtors, and the land registry. BIS Papers 64, 29–38.
Stanley, S., Lyons, R.C., Lyons, S., 2016. The price effect of building energy ratings in the Dublin residential market. Energy Eff. 9 (4), 875–885. https://doi.org/10.1007/s12053-015-9396-5.
Tabachnick, B.G., Fidell, L.S., 2012. Using Multivariate Statistics. Pearson Education, Inc, New Jersey.
Taltavull de la Paz, P., Perez-Sanchez, V.R., Mora-Garcia, R.-T., Perez-Sanchez, J.-C., 2019. Green premium evidence from climatic areas: a case in southern Europe, Alicante (Spain). Sustainability 11 (3), 686. https://doi.org/10.3390/su11030686.
Taruttis, L., Weber, C., 2022. Estimating the impact of energy efficiency on housing prices in Germany: does regional disparity matter? Energy Econ. 105, 105750 https://doi.org/10.1016/j.eneco.2021.105750.
The European Parliament and the Council of the European Union, 2003. In: Union, E (Ed.), Directive 2002/91/EC of the European Parliament and of the Council of 16 December 2002 on the Energy Performance of Buildings. Official Journal of the European Communities, pp. 65–71.
The European Parliament and the Council of the European Union, 2010. In: Union, E (Ed.), Directive 2010/31/EU of the European Parliament and of the Council of 19 May 2010 on the Energy Performance of Buildings. Official Journal of the European Communities, pp. 13–35.
Tuero Herrero, E., 2013. Selección de Modelos Multinivel en la Investigación en el Campo de la Educación. Departamento de Psicología. Universidad de Oviedo, p. 234.
Villca-Pozo, M., Gonzales-Bustos, J.P., 2019. Tax incentives to modernize the energy efficiency of the housing in Spain. Energy Policy 128, 530–538. https://doi.org/10.1016/j.enpol.2019.01.031.
Waddell, P., Berry, B.J.L., Hoch, I., 1993. Residential property values in a multinodal urban area: new evidence on the implicit price of location. J. Real Estate Financ. Econ. 7 (2), 117–141. https://doi.org/10.1007/BF01258322.
Wald, A., 1943. Tests of statistical hypotheses concerning several parameters when the number of observations is large. Trans. Am. Math. Soc. 54 (3), 426–482. https://doi.org/10.2307/1990256.
Warren-Myers, G., 2012. The value of sustainability in real estate: a review from a valuation perspective. J. Prop. Invest. Financ. 30 (2), 115–144. https://doi.org/10.1108/14635781211206887.
Wen, H., Tao, Y., 2015. Polycentric urban structure and housing price in the transitional China: evidence from Hangzhou. Habitat Int. 46, 138–146. https://doi.org/10.1016/j.habitatint.2014.11.006.
Yoshida, J., Sugiura, A., 2010. Which "greenness" is valued? Evidence from green condominiums in Tokyo, paper. Munich Personal RePEc Arch. 33.
Yoshida, J., Sugiura, A., 2015. The effects of multiple green factors on condominium prices. J. Real Estate Financ. Econ. 50 (3), 412–437. https://doi.org/10.1007/s11146-014-9462-3.
Zheng, S., Wu, J., Kahn, M.E., Deng, Y., 2012. The nascent market for "green" real estate in Beijing. Eur. Econ. Rev. 56 (5), 974–984. https://doi.org/10.1016/j.euroecorev.2012.02.012.