Spatial Econometric Analysis of Multi-family Housing Prices in Turin: The Heterogeneity of Preferences for Energy Efficiency

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Abstract. The positive impact of energy efficiency on property prices has been amply demonstrated in Europe by a large number of studies. However, much research has not considered the spatial nature of the data or has limited itself to considering it through fixed variables within econometric models based on hedonic price theory. To fill this gap in the literature, this study presents the spatial analyses by Geographically Weighted Regression (GWR) models of the Energy Performance Certificate (EPC) in Turin (Italy) using a dataset of apartments sales ads located in multi-family buildings. A number of models were created to study the interaction between energy class and age-related characteristics. The results indicate that the impact of EPC differs spatially and according to the age of construction of the buildings. The results are useful in the formulation of energy policies at the local scale, considering the location within the urban context, and the technological characteristics of the buildings according to the age of construction.

Keywords: Hedonic Pricing Method (HPM) · Ordinary Least Square (OLS) · Geographically Weighted Regression (GWR) · Energy Performance Certificate (EPC)

1 Introduction

In Europe, local governments are now interested in promoting the energy efficiency of buildings through targeted actions that require careful consideration of the economic resources allocated by the 2021 Recovery and Resilience Plans [1]. While the introduction of the Energy Performance Certificate (EPC), introduced by the European Directive on the Energy Performance of Buildings (EPBD) in 2002, is an important parameter for the definition of energy efficiency policies, it also represents one of the first actions at the European level to raise buyers' awareness of building energy consumption and environmental issues. In this regard, understanding potential buyers' perceptions of energy efficiency in terms of willingness to pay, through analysis of the residential real estate market, can support public actors in targeting policies on specific urban areas [2, 3]. Indeed, that energy consumption follows spatial patterns is obvious, as the building

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stock is not homogeneous, in terms of age of construction, structural and technological characteristics and, consequently, energy performance.

While this aspect has been investigated from the technological-energy point of view, it has been little explored from the economic one. Indeed, the positive impact of energy efficiency on house prices has been amply demonstrated in Europe by a large number of studies based on econometric models. However, few studies have considered the spatial nature of the data, often limiting themselves to considering it through fixed variables within models based on hedonic price theory.

In this context, the present study focuses on the analysis of a sample of multiple residential buildings in Turin (Italy) to investigate how building price varies with energy efficiency within municipal boundaries. Specifically, Geographically Weighted Regression (GWR) models were applied to study the spatial heterogeneity of building characteristics in terms of energy efficiency and the interaction of EPC with building age.

The paper is organized as follows. After the "Introduction," the "Research Background on EPC Investigation" section explores research in studies concerning applications of revealed preference methods in the energy sector. The "Methods" section presents the econometric models used. The case study, properties sample and initial descriptive analyses are presented in the "Application" section. The results are presented and discussed in the "Results" section. The "Conclusions" section summarizes the implications, limitations, and conclusions.

2 Research Background on EPC Investigation

One of the most widely used econometric approaches to analyzing the housing market is the hedonic pricing method (HPM) proposed by Rosen [4]. This method has been widely used in the field of analyzing consumer preferences for energy attributes of dwellings, by investigating the impact of sustainability certificates, such as the Building Research Establishment Environmental Assessment Method (BREEAM), the Leadership in Energy and Environmental Design (LEED), the Green Mark, and the Energy Performance Certificate (EPC).

The introduction of the EPC scheme [5], along with the Energy Performance Index (EPI), are the most widely used indicators in Europe in studies in this field of research to describe the energy performance of buildings. In 2012, Kok and Jennen proposed one of the first European studies to investigate the effect of EPC on real estate sales [6]. Rosen's theoretical explanation of HPM was applied to the office market in the Netherlands. The results show that non-green buildings are 6.5% lower than offices in the upper EPC class. Cajias and Piazolo [7] applied a hedonic price model to test the appreciation of a high EPC level in Germany. High prices are confirmed for buildings in high energy classes with a 32.8% increase in property value. In Italy, Fregonara et al. [8] and Dell'Anna et al. [9] used hedonic regression to study the impact of EPC in the Turin housing market. Both studies suggest that there is a green premium linked to energy class. However, other studies have shown that there was no positive relationship between the energy class and real estate prices. In Norway, Olaussen et al. [10] showed that there is no price premium guaranteed by a high EPC. In their view, the high price premium is related to

the aesthetic quality of the buildings and not to better energy performance. Cerin et al. [11] did not find a relationship between EPC and high price in Swedish private buildings. However, this result is not confirmed by Högberg [12] who found a positive influence of energy performance improvements on selling prices in Stockholm in those same years. Thus, most of the literature consulted suggests that there is consumer willingness to pay for green buildings. Other studies have shown more moderate results, with minor or no effects of EPC. However, exploring this phenomenon in space could clarify why the impact of EPC is not significant or if uneven over the urban context.

One of the most highlighted issues in these studies refers to the need to improve the inclusion of spatial and temporal dimensions in the model, which are currently under-investigated [13–15]. The inclusion of fixed location variables partially solves the spatial problem, as they do not correctly delineate the distribution of the relationship between building characteristics and price, leading to biased coefficient estimates. Barreca et al. [16] investigated the influence of energy performance and different characteristics on property prices by performing spatial analyses on a sample of dwellings listed on the Turin housing market and on different subsamples. Exploratory Spatial Data Analyses (ESDA), Ordinary Least Squares (OLS) and Spatial Error Models (SEM) are applied first on the whole data sample and then on three different subsamples highlighting the presence of spatial effects in different submarkets. Marmolejo-Duarte et al. [17] applied a Geographically Weighted Regression (GWR) model to test the spatial heterogeneity of EPC ranking coefficients in the Barcelona metropolis (Spain). Their results found that energy efficiency is not a priority in some areas in relation to other residential and local attributes, making the coefficient for local EPC ranking erratic. McCord et al. [18] presented a spatial analyses of EPCs through GWR models using transaction data for the Belfast metropolitan area. The authors tested for spatial effects between EPCs and house prices through several spatial tests and through a series of models developed to test for the existence of spatial dependence and to determine if there are spatially correlated effects through autoregressive models. The authors showed that there are price differences in the spatial variation of EPCs with price effects consistent with building type and building age.

In line with the reviewed studies, this paper contributes to this recent literature that investigates the heterogeneity of the relationships between property characteristics, with a focus on energy performance and the interaction with building age, and sale or offer prices. Like other studies, we propose both traditional hedonic models based on the OLS method and local regression models based on the GWR to examine spatial differences in terms of the composition of the housing stock. The goal is to provide guidance to public decision makers to design energy policies in line with consumer behavior through maps showing the relationship between price, EPC, and age of building construction, following the McCord et al. [18] work.

3 Methods

According to the HPM approach, a property can be like a set of attributes, which can bring benefits to the consumer. These benefits are part of the hedonic price function, as

shown in the Eq. (1):

$$P = f(x_1, x_2, ..., x_n) \tag{1}$$

where P is the market price, $x_1, x_2, ..., x_n$ are the property characteristics. The regression technique helps to find the relationship between the price and the different properties of the building. In the linear model, the form of the hedonic function is as follows (2):

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + ... + \beta_n x_n + \varepsilon \tag{2}$$

where β_0 represents the intercept of the function, β_1 is the coefficient of the variable x_1, and ε is the stochastic error term.

In the linear model, the OLS method allows the determination of the function coefficients [19]. One of the limitations of OLS-based regression is that spatial autocorrelation and spatial dependency issues are not considered [20, 21] and a stationary process is usually assumed. In this setting, the parameters estimated by the model (β, ε) can only vary using different and independent subsamples. Under the assumption of dealing with a single sample, this problem was addressed by including the micro area (statistical or cadastral) as a dummy variable [22]. These approaches raise many questions, both from the point of view of sample size (which is never balanced for all areas) and from the point of view of stationarity and the application of the relevant estimates in institutional or market settings.

Some researchers have studied these effects by proposing the application of spatial regression models. Osland worked through the testing of various spatial models (Geographically Weighted Regression, semiparametric analysis, and mixed spatial Durbin model) as well as a discussion of the application and interpretation of diagnostic tests aimed at choosing the correct spatial specification [23]. Her comparative analysis shows that these spatially explicit models far outperform a traditional OLS model. Fotheringham et al. [24], Brunsdon and Fotheringham [25] proposed GWR as a spatial statistical technique that recognizes that traditional 'global' regression models may be limited when the elements influencing the dependent variable vary according to context. In the real estate context, the GWR model can capture the spatial heterogeneity of the real estate market, which is inevitably influenced by urban elements that are not uniformly distributed across urban space. The GWR model is based on a set of local linear models that is calibrated by considering data from a set of neighboring observations. The result is an estimate of the position characteristics for each observation in the model, as well as a single bandwidth parameter that provides insights into the geographical scale of the effects. A GWR model is specified as Eq. 3;

$$y_i = \beta_{i0} + \sum_{k=1}^{p} \beta_{ik} x_{ik} + \varepsilon_i i = 1, \ldots, n, \tag{3}$$

where y_i is the dependent variable at location i, β_{i0} is the intercept coefficient at location i, x_{ik} is the k-th explanatory variable at location i, β_{ik} is the k-th local regression coefficient for the k-th explanatory variable at location i, and ε_i represents the random error term

associated with location *i*. GWR estimator for local parameter estimates become in matrix form as Eq. 4;

$$\widehat{\beta}(i) = \left[X'W(i)X\right]^{-1}X'W(i)y \tag{4}$$

where X is a n by k matrix of explanatory variables, $W(i)$ is the n by n diagonal weights matrix that weights each observation according to its distance from the position i, $\widehat{\beta}(i)$ is a k by 1 vector of coefficients, and y is a k by 1 vector of observations of the dependent variable.

The GWR model is advantageous in the analysis of spatial heterogeneity for two main reasons in housing market analysis. First, this method allows to test for spatial variation of parameters in the analysis of implicit house prices [26]. The GWR model also performs better than OLS in terms of explanatory power and predictive ability [27]. Secondly, the GWR model can provide detailed parameters of each sampling point and visualize the spatial pattern of the housing market using GIS (Geographic Information System) software to intuitively and clearly represent the spatial difference of marginal prices [28].

4 Application

The present study follows a multi-step methodology. First, data containing the prices and characteristics of properties were collected from immobiliare.it, the largest Italian site where real estate listings are collected, for the most part, from local agencies. The period considered refers to the years 2014 to 2021, representing a cross-sectional dataset of the Turin city area (Fig. 1). The data collection mainly concerned the multi-family building typology as it is the predominant housing type in the city, for a total of 79,347 observations. The second step was the definition of the explanatory variables. The data

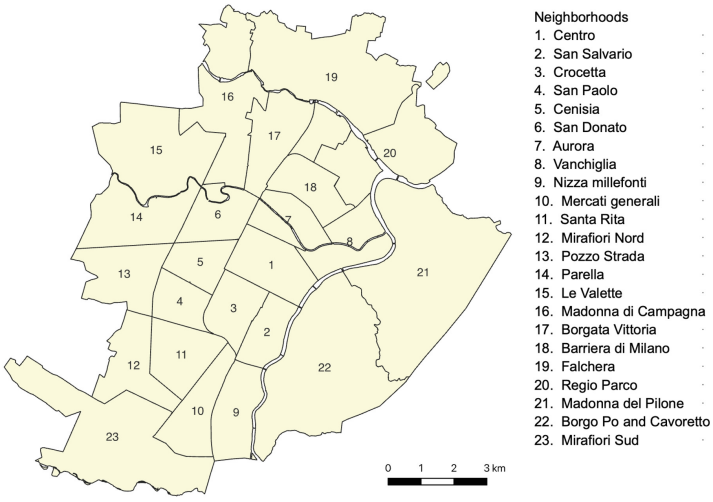


Fig. 1. Turin's neighborhoods.

were subsequently exported to SPSS© statistical software [29] to develop OLS models, and to MGWR© to calibrate GWR models [30].

In cases where there is one or more missing information within a statistical unit (e.g., a row in the data set), regression analysis involves eliminating it. Since many observations were missing some information of the features in the dataset, it was necessary to limit the number of variables to be considered in the hedonic model and to eliminate incomplete cases. In addition, since the research aims to investigate the spatial effect of the impact of energy performance, great attention was paid to the availability of EPC information for all observations. After eliminating incomplete records and outliers, the final dataset consisted of 25,245 sales announcements. As the spatial statistical analysis limits the analysis to spatially unduplicated data, it was not possible to include housing units located in the same building, and therefore with the same geographical coordinate. This limitation led to the selection of one transaction per geographical point. In addition, given the time required to calculate GWR models, 20% of the observations were randomly retained to develop the analysis, i.e., 5,899 observations.

The variables studied within the regression models relate to the structural characteristics of the apartment (floor area, dwelling level, maintenance status, EPC, age of construction, and year of advertisement publication). Some initial variables were transformed from their original scale to ordinal variables so that they could be included in the model. Initially expressed as a continuous variable, the housing level variable was categorized into a point scale as follows: –1 if the floor is basement or crawlspace; 0 if ground floor; 1 if floor is mezzanine, 1^{st} or 2^{nd}, 2 if floor 3^{rd} or 4^{th}, 3 if 5^{th} floor or greater. Considering the data included in the database, the average number of floors is about 3 floors. A breakdown of the ordinal variable in this way should make it possible for the model to understand the consumers' appreciation of the different dwelling levels. The state of maintenance is composed of an ordinal variable ranging from 0 to 3, where 0 indicates an apartment in need of renovation, 1 in good condition, 2 renovated, 3 new/under construction). The market segment indicates the architectural quality of the property in which the apartment is located, and it is composed of an ordinal variable with 4 levels: 0 for economy class, 1 for medium class, 2 for high class, 3 for very high class. The continuous variable of year of construction was also reduced in age classes following TABULA classification which groups buildings based on the technological characteristics of the building envelope and thermal systems (before 1900, between 1901–1945, between 1946–1960, between 1961–1975, between 1976–1990, after 1990) [31]. The ordinal scale proposed by the European Commission was used to measure the impact of the energy label. In detail, the 12-level scale was reduced to 7, including levels above A in a single level, where 1 stands for properties in G and 7 in A. The proportions of the housing stock by EPC classification are quite similar to the Italian picture. It is worth noting, however, that houses with A and B classification represent the smallest portion of the Turin market (5.1%). The largest share of the market is covered by intermediate energy classes C to E (45.6%), and by buildings in classes F and G (49.3%). The spatial distribution of buildings categorized according to EPC makes it clear that the most efficient assets (class A-B) are scattered throughout the urban territory of the city of Turin, with a greater prevalence in the suburbs. On the other hand, the remaining building stock comprises the remaining classes and is spread throughout the city with

a higher prevalence of the lowest classes (E-G) in the northern and southern part of the city (Fig. 2).

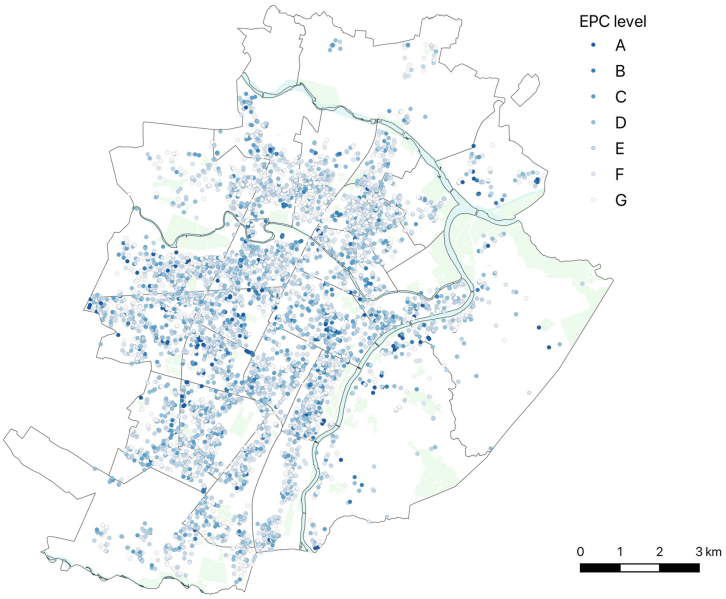


Fig. 2. Properties in the reduced sample categorized by energy class level.

Sample size across property attributes was studied to confirm representation within the dataset of sales transactions (Table 1). In terms of property age, the most recently built properties are the least representative, revealing that 9.4% of the sample data includes real estate properties built after 1990. Newer buildings (post-1960) account for 29.2% of the sample, while postwar housing accounts for 36.8%. This portion of the housing stock represents the phenomenon of building densification that occurred in Turin during the post-war recovery period.

Table 1. Sample representativeness according construction period.

Age	Frequency (No.)	% of total	Age	Frequency (No.)	% of total
Before 1900	588	10.0	Between 1961–1975	1564	26.5
Between 1901–1945	866	14.7	Between 1976–1990	158	2.7
Between 1946–1960	2169	36.8	After 1990	554	9.4

Table 2 presents a summary of the descriptive statistics of the data. The average price of the sample properties is 175,322 €, revealing a high variance (SD 173,627 €). The average floor size is 91.32 m^2, with an average EPC of 2.72, which is in line with the broader average residential range rated E.

Table 2. Descriptive statistics of variables.

Variables	Measure	Min	Max	Mean	SD
Price (€)[a]	Scale	14,900	2,250,000	175,322.64	173,627.621
Floor area (m^2)	Scale	28	1000	91.32	49.911
Dwelling level	Ordinal	– 1	3	1.63	0.970
Maintenance status[b]	Nominal	0	3	1.33	0.798
Market segment[c]	Nominal	0	3	1.42	1.007
EPC[d]	Ordinal	1	7	2.72	1.526
Before 1900[e]	Nominal	0	1	0.10	0.300
Between 1901–1945[e]	Nominal	0	1	0.15	0.354
Between 1946–1960[e]	Nominal	0	1	0.37	0.482
Between 1961–1975[e]	Nominal	0	1	0.27	0.441
Between 1976–1990[e]	Nominal	0	1	0.03	0.161
After 1990[e]	Nominal	0	1	0.09	0.292
Car parking	Scale	0	3	0.34	0.756
Lift[e]	Nominal	0	1	0.72	0.451
Year[f]	Ordinal	1	8	6.17	1.697
[a]Dependent variable					
[b]Maintenance status (0 = To be restored; 1 = Good; 2 = Restored; 3 = New/Under construction)					
[c]Market segment (0 = Low; 1 = Medium; 2 = High; 3 = Very high)					
[d]Energy Performance Certificate (A = 7; B = 6; C = 5; D = 4; E = 3; F = 2; G = 1)					
[e]1 Yes, 0 otherwise					
[f]Advertising year (2014 = 1; 2015 = 2; 2016 = 3; 2017 = 4; 2018 = 5; 2019 = 6; 2020 = 7; 2021 = 8)					

5 Results

5.1 Global Regression Model

The semi-logarithmic OLS model (Table 3) incorporates the EPC score and the age of construction of the buildings. The overall explanation of the model shows a relative

performance (R^2) of 72.7%. All coefficients generally meet expectations in terms of sign and significance. The coefficient estimates show that floor area is the most influential feature ($t = 83.646$, $p < 0.01$), as expected. This means that a one-square meter increase in the commercial floor area of housing adds 0.9% value to the property. The results show that the top floors are worth more (coefficient 0.027). For architectural qualities, both the coefficients of property condition and maintenance status are positive and show percentage effects of 10.3% and 10.6% for a higher level, respectively. Increasing the energy class level leads to a 5% increase in property value. Regarding property age, the results show that older properties have more value - likely because older properties tend to be larger and of greater historical value ($\beta_{before900} = 0.211$, t-value = 8.255, p-value < 0.01) than newer properties. In contrast, the coefficients for the other age groups are negative. The availability of a garage belonging to the housing increases the value of the property by 3%. The presence of an elevator inside the building adds a value of 23.6%. The variable referring to the year of publication of the advertisement, on the other hand, registers a negative coefficient value, reflecting the market trend that has characterized the Turin real estate market.

Table 3. OLS model results (dependent variable = ln price).

	β	SE	t-value	p-value	VIF
Intercept	29.431	5.965	4.934	0.000	
Floor area	0.009	0.000	83.646	0.000	1.274
Dwelling level	0.027	0.005	5.074	0.000	1.078
Maintenance status	0.103	0.007	14.346	0.000	1.312
Market segment	0.106	0.006	18.912	0.000	1.284
EPC	0.050	0.004	12.783	0.000	1.433
Before 1900	0.211	0.026	8.255	0.000	2.358
Between 1901–1945	– 0.061	0.025	– 2.459	0.014	3.069
Between 1946–1960	– 0.116	0.022	– 5.217	0.000	4.647
Between 1961–1975	– 0.116	0.022	– 5.257	0.000	3.792
Between 1976–1990	– 0.092	0.036	– 2.583	0.010	1.339
Car park	0.030	0.007	4.086	0.000	1.238
Lift	0.236	0.013	18.871	0.000	1.281
Year	– 0.009	0.003	– 3.201	0.001	1.012
$R^2 = 0.727$		SE = 0.3825			
Number of observations: 5,899		Mean dependent variable: 11.70			
VIF = Variance inflation factor		SE = Standard error			

The next model involves modifying the previous one by including interacting variables to examine the effects of EPC scores for each property age (Table 4). The interaction between age and EPC shows that properties prior to 1900 and constructed between 1901

and 1945 are positive. The remaining properties built after 1945 show a negative impact that is statistically insignificant. Interestingly, age classifications suggest that older (pre-1900) properties show a higher price effect ($\beta_{before900} = 0.099$, t = 16.568, p-value < 0.01), which may be explained by the fact that these properties are larger and have historic-architectural features that are valued in the market. These results may reflect the complex relationships in the market that can influence consumer preferences [32]. For example, an energy-efficient home located in a more desirable area may illustrate a high premium or discount due to the location effect, not the level of energy performance.

Table 4. OLS interactive model results for property age (dependent variable = ln price).

	β	SE	t-value	p-value	VIF
Intercept	34.897	6.086	5.734	0.000	
Floor area	0.009	0.000	81.958	0.000	1.273
Dwelling level	0.026	0.005	4.756	0.000	1.075
Maintenance status	0.145	0.007	22.102	0.000	1.060
Market segment	0.118	0.006	20.846	0.000	1.262
Before 1900 x EPC	0.099	0.006	16.568	0.000	1.240
Between 1901–1945 x EPC	0.030	0.006	5.057	0.000	1.289
Between 1946–1960 x EPC	0.006	0.004	1.314	0.189	1.465
Between 1961–1975 x EPC	0.003	0.005	0.629	0.529	1.408
Between 1976–1990 x EPC	0.006	0.010	0.607	0.544	1.072
Car park	0.050	0.007	6.882	0.000	1.165
Lift	0.249	0.012	19.984	0.000	1.222
Year	– 0.012	0.003	– 4.046	0.000	1.008
$R^2 = 0.715$		SE = 0.3911			
Number of observations: 5,899		Mean dependent variable: 11.70			
VIF = Variance inflation factor		SE = Standard error			

5.2 Local Regression Results

Consistent with other studies, OLS-based estimates have shown some important results on the green premium associated with effective properties. In this section, we explore the fluctuation of real estate market estimates in the urban environment. In detail, we test for the variable nature of EPCs as highlighted in Table 5. The first step of the GWR requires determining the value of the optimal bandwidth with iterations to obtain the minimum AICc. MGWR© software was used to calculate local parameter estimates [30]. The weighted matrix was formed using the adaptive bisquare function since the observations are not spatially uniformly distributed. The result of the iteration produced an AICc

of 2284 with a bandwidth value of 504 neighbors. The GWR models showed better performance than OLS model, with $R^2 = 0.864$. The results reveal the existence of a clear heterogeneity and spatial variation by property construction era: properties built before 1900 show a negative price effect up to the median statistical value. While properties built between 1901 and 1975 reveal a negative price effect up to the third quartile, with a positive effect in the top value. Properties built between 1976 and 1990 show a consistent negative effect. These characteristics show distinct concentrations clustered in space presenting the complex picture of housing market composition. In terms of the effects of EPCs, the varying degree of impact on value ranges from a negative 2.85%, to the maximum effect positively affecting prices of 9.34% (Fig. 3). This is a noteworthy result as the average market coefficient for the OLS models suggests that there appears to be a uniform positive effect of 5% within the City of Turin market. In this sense, the OLS estimates may be misleading in terms of being a more truthful representation of the influence of EPC on market value. In terms of spatial variability, it is noteworthy that only the lowest value of the coefficient for EPCs is negative, while the bottom quartile shows a value of 3.4%. Focusing on the statistical-descriptive distribution of implied prices, the effects seem to be apparently premium-free at the lower end of the market. Instead, they appear to have a larger effect in the top quartile and the top value range (4.88 and 9.34 respectively).

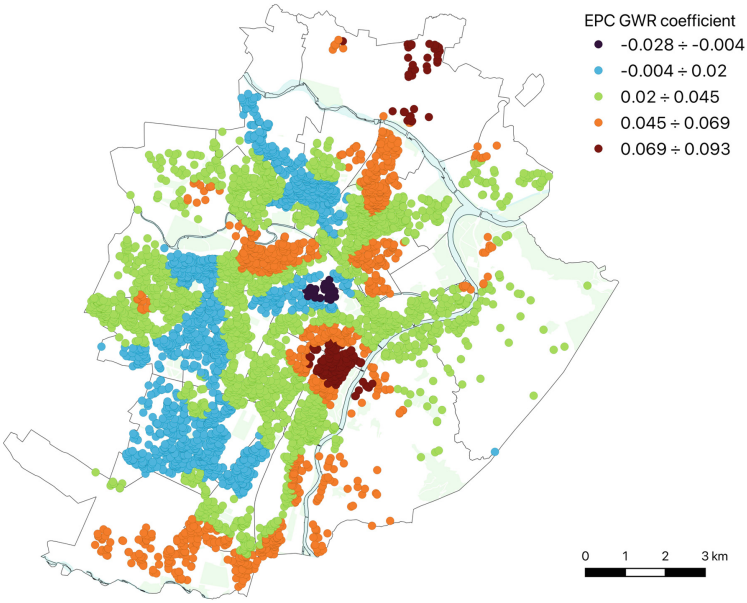


Fig. 3. Geographically Weighted Regression (GWR) energy performance certificate (EPC) level coefficients (equal interval classification of minimum and maximum value).

The results, as mentioned earlier, can be represented graphically using GIS. As noted in Fig. 3, the EPC coefficient appears to show differential price effects within the city of Turin. In Mirafiori, San Donato, southeast Aurora, and Barriera di Milano

neighborhoods, and toward the southeast of the city center, energy efficiency appears to be a clear premium. The value of EPC coefficient, while positive, is small in the rest of the city. In contrast, there is only a small portion in the central part of the market area where energy efficiency seems to have a discount effect and is valued negatively in the market.

Further refining the GWR model to test the spatial interaction between structural characteristics for property age and EPC, we also show some heterogeneous effects of EPC (Table 6). Regarding the spatial interaction between property age and EPC score, pre-1900 properties show an effect on price ranging from –32% to 53%, with a negative effect observed only at the lowest value and a positive effect starting from the lowest quartile. Properties built between 1946 and 1960, and between 1961 and 1975 show a negative price effect at the lowest level. The coefficients become positive from the first quartile, also revealing a smaller range of impact than for older buildings. For properties built between 1901 and 1945, and between 1976 and 1990, the range of estimated coefficients is negative down to the first quartile. Examining the interactions between property age and EPC, some notable patterns emerge. The pre-1900 age category shows two distinct market geographies (Madonna di Campagna and Mirafiori Nord) where there appears to be a negative effect on market prices (Fig. 4), with a positive premium evident in the southwest (Mirafiori Sud).

Table 5. GWR model results.

	Minimum	Lower quartile	Median	Upper quartile	Maximum
Intercept	– 101.7108	41.1928	50.2950	60.6815	144.3426
Floor area	0.0054	0.0092	0.0106	0.0121	0.0160
Dwelling level	– 0.0493	0.0477	0.0583	0.0687	0.0994
Maintenance status	0.0469	0.0948	0.1170	0.1349	0.2181
Market segment	0.0313	0.0478	0.0643	0.0952	0.2132
EPC	– 0.0285	0.0346	0.0418	0.0488	0.0934
Before 1900	– 1.3641	– 0.3462	– 0.2539	0.2659	0.8528
Between 1901–1945	– 0.5154	– 0.3660	– 0.2792	– 0.2262	0.2031
Between 1946–1960	– 0.3751	– 0.2869	– 0.2414	– 0.2050	0.1910
Between 1961–1975	– 0.4159	– 0.2623	– 0.2291	– 0.1930	0.1856
Between 1976–1990	– 0.7354	– 0.3797	– 0.3228	– 0.2666	– 0.1756
Car park	0.0417	0.0557	0.0625	0.0781	0.1200
Lift	0.0724	0.1644	0.2005	0.2460	0.4267
Year	– 0.0664	– 0.0277	– 0.0220	0.0237	0.0558
$R^2 = 0.864$			Residual sum of squares = 429.944		
Number of observations: 5,899			Mean Dependent variable: 11.70		
AICc = 2248.62			Bandwidth = 504		

Interestingly, as noted in Table 6, the Before 1900 * EPC show the negative association at the lower end of the price distribution, signaling that these two respective neighborhoods are perhaps more socioeconomically disadvantaged. Buildings built between 1901 and 1960 show distinct areas recognizable in terms of positive prices in San Salvario, San Donato, Falchera, and the area to the west. The negative association is more pronounced in the north, downtown, and hillside areas, highlighting that EPCs for properties built between 1901–1945 include a price effect ranging from –9.24% to 11.6% (Table 6). For housing from the period between 1961 and 1975, the effect is positive starting at the lower quartile value, inferring that these properties tend to have a positive EPC effect in all price strata. In terms of spatial representation, there are also localized concentrations of both positive and negative effects with distinct enclaves in the west, north, south, and premiums, with more negative enclaves observed in the west of the city (Fig. 4). For properties built between 1976 and 1990, there is a premium in Aurora and Barriera di Milano, and between Parella and Campidoglio neighborhoods.

Table 6. GWR model results for testing the interaction between building age and EPC.

	Minimum	Lower quartile	Median	Upper quartile	Maximum
Intercept	– 111.1155	43.2291	53.9089	69.3565	129.6445
Floor area	0.0055	0.0092	0.0106	0.0121	0.0160
Dwelling level	– 0.0447	0.0491	0.0594	0.0687	0.0980
Maintenance status	0.0614	0.1269	0.1533	0.1736	0.2318
Market segment	0.0325	0.0508	0.0648	0.0963	0.2097
Before 1900 * EPC	– 0.3299	0.0476	0.0841	0.1557	0.5369
Between 1901–1945 * EPC	– 0.0924	– 0.0478	0.0331	0.0537	0.1160
Between 1946–1960 * EPC	– 0.0943	0.0266	0.0474	0.0633	0.0840
Between 1961–1975 * EPC	– 0.0484	0.0333	0.0390	0.0485	0.0710
Between 1976–1990 * EPC	– 0.1683	– 0.1037	0.0882	0.0972	0.1435
Car park	0.0428	0.0564	0.0648	0.0812	0.1411
Lift	0.0707	0.1874	0.2210	0.2590	0.4089
Year	– 0.0591	– 0.0314	– 0.0256	0.0219	0.0605
$R^2 = 0.855$			Residual sum of squares = 457.44		
Number of observations: 5,899			Mean dependent variable: 11.70		
AICc = 2533.99			Bandwidth = 504		

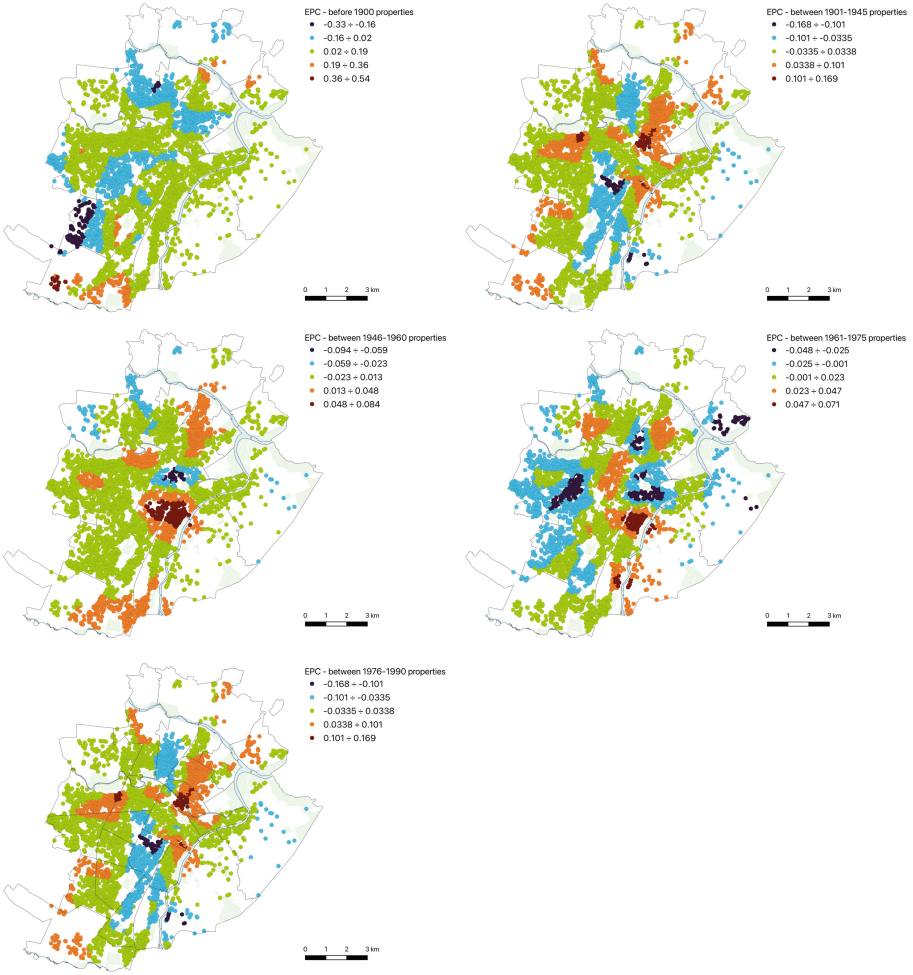


Fig. 4. Geographically Weighted Regression (GWR) property age and energy performance certificate (EPC) level coefficients.

6 Discussion and Conclusions

The Energy Performance Certificate (EPC) is an important tool for improving the energy performance of buildings. It plays a central role in the context of the Energy Performance of Buildings Directive (EPBD), which requires Member States (MS) to take the necessary steps to establish a comprehensive certification system. This study contributes to the real estate literature by presenting an application of the hedonic pricing method (HPM) that evaluates the effect of EPC-derived energy labels on the value of the Turin real estate market through global and local regression models. The developed models demonstrated noteworthy results on the market price of energy performance, which are reflected in the spatial distribution of the estimated energy label coefficients. The OLS

model highlighted the positive impact of the EPC, concluding that the higher the level, the greater the capitalized premium in the price of the property. OLS models also show that there is no increasing distribution of preferences with respect to age of construction: properties built before 1900 are more highly valued than those built from 1901 onward. A key finding demonstrated by the OLS model that makes EPC interact with building age is that consumers recognize the energy efficiency potential of buildings built before 1945. GWR models provide evidence of how prices of multifamily properties vary within city boundaries based on energy performance. Local models have shown that spatial variability in preferences is distributed across local scales based on short distances. The GWR model including the EPC label as an independent variable showed spatial variation for energy performance. Although the impact is positive on almost the entire city of Turin, with peaks of appreciation in the neighborhood of San Salvario and Rebaudengo north and Falchera. Only in the city center is an area identified where the impact of EPC is negative. Modifying the model specification by including interactive variables to examine the effects of EPC scores for each age, pre-1945 properties report statistically significant positive effects. Examination of the interactions between building age and EPC reveals some noteworthy topographic market structures. The pre-1900 age category shows two distinct market geographies where there appears to be a negative effect on market prices, with a positive premium evident on the rest of the city. Buildings constructed between 1901 and 1945 also show clusters with negative marginal prices. For housing from 1946–1975, the effect on prices is evident. Since the effect is positive from the lower quartile value onwards, it means that these buildings tend to have a positive EPC effect in all price strata.

These results are of particular interest to policymakers to ensure that differences in perceived value for EPC are aligned with energy efficiency policies [33, 34]. In fact, the results of the study could be useful to public policymakers in identifying areas and building types where energy efficiency operations in the building sector should be promoted through incentives and ad hoc policies to accelerate the green transition process.

Future research should include additional variables to be able to better reflect the energy performance of buildings such as the EPI. Indeed, the continuous variable describing energy efficiency could better match the continuous dependent variable of price, providing a more deterministic relationship.

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