

# Energy Performance Certificates and Housing Transaction Prices: Empirical Evidence from Market Data Analysis

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**Abstract.** In recent years, the intersection between real estate market dynamics and environmental sustainability has gained increasing attention, particularly in light of the European Union's regulatory efforts to decarbonize the building sector. Energy Performance Certificates (EPCs), initially conceived as informational tools, are now emerging as significant drivers of housing prices and investment decisions. This study investigates the impact of EPCs on real estate transaction prices within the urban context of Turin, Italy, with a specific focus on spatial effects often neglected in traditional analyses. Using a dataset of over 5,000 property listings from 2022–2023, a Spatial Error Model (SEM) is implemented to capture spatial autocorrelation and improve model accuracy. The results reveal a statistically and economically significant "green premium" for high-efficiency dwellings (EPC A and B–C) and a corresponding "brown discount" for inefficient properties (EPC F–G). These findings not only validate the role of EPCs in price formation but also align with the broader objectives of the EU Green Deal and the Green Asset Ratio (GAR), which increasingly integrates energy performance into financial valuation. The study offers novel insights into the spatial valuation of sustainability and suggests that market forces, coupled with regulatory instruments, are reshaping investment patterns in the built environment.

**Keywords:** Energy Performance Certificates · Housing Prices · Spatial Econometric Models

## 1 Introduction

In the last decades, the influence of energy-building performance on pricing processes has been deeply explored in European and international contexts due to the growing relevance of environmental policies and their related norms and regulations. The role of Energy Performance Certificates (EPCs) – a measure of the building performance adopted by several governments - in the real estate market has evolved significantly over the years, shaping both property valuation methodologies and financial decision-making processes. More precisely, in the Italian context, from their introduction EPCs have been increasingly recognized as a key factor influencing market value [1, 5, 26,

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31], rental prices, and investment attractiveness [10, 27]. Recent regulatory and updates at the European level, particularly EU Directive 2024/1275 on the energy performance of buildings, have further reinforced the importance of environmental sustainability in the building construction sector and, consequently, in the real estate market sector, introducing new challenges for property owners, investors, and financial institutions.

Besides, the growing emphasis on environmental, social, and governance (ESG) factors in real estate finance has led to the development of key performance indicators (KPIs) such as the Green Asset Ratio (GAR), which financial institutions must disclose as of January 1, 2024 [24]. The GAR measures the proportion of credit assets financing activities aligned with the EU Taxonomy for sustainable finance, highlighting the need for more detailed data on the energy performance of buildings. Real estate assets that meet the environmental standards introduced by GAR taxonomy (such as energy-efficient buildings or those undergoing substantial renovations to improve sustainability) are more likely to attract green financing and institutional investments. As a result, market participants are increasingly incentivized to develop, retrofit, or acquire properties that comply with green criteria, potentially reshaping investment strategies and driving broader changes in the built environment. In particular, the residential real estate sector plays a crucial role in this framework, as real estate-backed loans (Fig. 1) represent 93.6% of eligible assets within financial institutions [23].

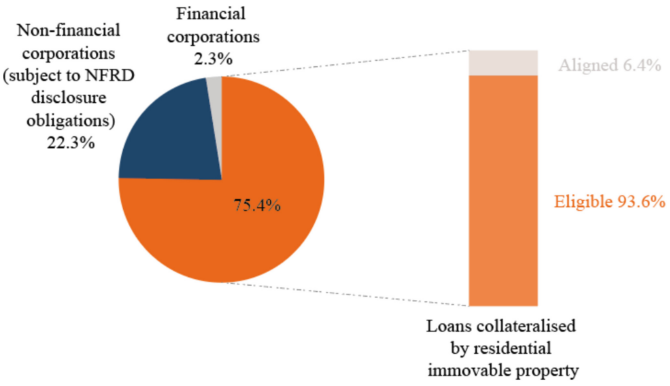


**Fig. 1.** Breakdown of eligible and aligned shares of the stock by macro-components as of December 31, 2023, Elaboration from European Banking Authority, 2022

The EPC is a crucial tool in assessing the eligibility of real estate assets under the EU Taxonomy, and thus their inclusion in the GAR. The EPC provides standardized information on a building's energy efficiency, a core criterion for determining whether a property qualifies as environmentally sustainable. Consequently, the EPC functions as a key data source for financial institutions calculating their GAR, reinforcing the role of energy performance as a central pillar of sustainable finance in the real estate market sector.

Despite the growing importance of EPCs in the financial and regulatory landscape, the availability and granularity of EPC data remain key challenges [22].

The share of "aligned" residential properties—those meeting the highest energy efficiency standards—remains relatively low due to factors such as:

- The absence of EPC data in real estate transactions and mortgage assessments [28];
- The lack of systematic digitalization in energy certification records [36];
- The exposure of the European housing stock to older, less efficient buildings that do not fall within the top 15% in terms of energy performance [25].

To address these issues, recent initiatives in real estate digitalization and data analytics have focused on improving EPC-based property valuation models. Real estate platforms such as Immobiliare.it are now integrating Automated Valuation Models (AVMs) to refine price predictions based on energy efficiency levels [40]. Similarly, financial institutions increasingly adopt data-driven approaches to assess EPC-related risks and opportunities within their portfolios [38].

In this context, this paper aims to explore the impact of EPCs on real estate transaction prices, analysing how the market perception of energy certification has changed over time and how advancements in database structures and analytical models are influencing real estate valuation. Unlike previous studies that focused on case-specific results, this research emphasizes the broader methodological evolution in EPC data integration and its implications for both real estate markets and financial compliance with EU sustainability directives.

Understanding the influence of EPCs in real estate transaction prices is essential for multiple reasons, particularly in the current European regulatory and financial landscape. The increasing stringency of EU sustainability policies is pushing both property buyers and investors to reconsider the weight of energy efficiency in their decision-making processes [37]. Several studies have demonstrated that properties with higher EPC ratings tend to command higher sales prices and shorter time on the market, as energy-efficient properties offer lower operational costs and increased comfort [27, 30]. By analysing transaction prices, it is possible to quantify the premium associated with EPCs, and understand how market segments react to regulatory and economic changes [14–16, 35]. As banks and financial institutions are now required to disclose their Green Asset Ratio (GAR), the role of EPCs extends beyond the real estate market sector into the financial market. Mortgage-backed loans and real estate assets constitute a huge portion of banks' portfolios, meaning that the energy efficiency of collateralized properties directly impacts a financial institution's GAR score and, consequently, its attractiveness to investors focused on ESG compliance [23].

Analysing the impact of EPC data on real estate transaction prices helps anticipate how regulatory changes shape lending policies, credit risk assessments, and mortgage pricing. Cities and municipalities also leverage EPC data to shape urban planning and building retrofitting policies. Understanding how EPCs influence real estate market trends can support policymakers in designing incentives for energy-efficient renovations, green mortgages, and subsidies to accelerate the transition toward a more sustainable housing stock [33]. The availability and quality of EPC data remain key limitations in many European markets, affecting the accuracy of property valuation models and real estate investment risk assessments [17]. Analysing how new data-driven methodologies, such as machine learning algorithms for price prediction and blockchain-based

EPC registries, are reshaping the market can provide valuable insights into future trends and policy effectiveness [31].

Given the rapid evolution of regulations, financial mechanisms, and digital tools surrounding EPCs, it is crucial to analyse their impact on real estate transaction prices. This study will contribute to the existing literature by exploring how EPC-driven market perceptions have changed over time and evaluating the potential of emerging data integration methodologies. Doing so will offer valuable insights for policymakers, investors, and real estate professionals navigating the evolving landscape of sustainable property markets.

## 2 Materials

In past studies, the impact of Energy Performance Certificate (EPC) labels on real estate prices in the Turin housing market using different datasets and methodologies was investigated (Table 1.). These previous studies were conducted availing the data set implemented during decades by the Turin Real Estate Market Observatory - TREMO (https://oict.polito.it/). Established in 2000 through a partnership between the Politecnico di Torino and the Municipality of Turin, and subsequently also by the Turin Chamber of Commerce, for decades the Observatory has continuously monitored and analyzed housing prices along with their intrinsic and extrinsic characteristics across different territorial segments of the city, which correspond to distinct real estate submarkets. Recently, TREMO evolved in the "Turin Real Estate Market Observatory – Research" (TREMO-R), a Research Center in the Architecture and Design Department of the Politecnico di Torino.

In a first study [28] a dataset of 577 property listings from 2012 was analyzed, focusing on the effect of EPC labels on listing prices through a hedonic regression model (Ordinary Least Squares), incorporating additional property characteristics such as location, housing attributes, and apartment features.

Then, a second study [27] examined a sample of 1,131 transactions from 2011 to 2014, assessing EPC labels' influence on listing and transaction prices. This study employed a hedonic pricing model that included variables such as construction period, EPC ratings, and apartment-specific features. A third study [10] analysed a more extensive dataset of 2,092 housing properties listed in Turin between 2015 and 2018, applying spatial econometric models (Spatial Error Model) to assess the joint effects of EPC labels, architectural and typological attributes, and location on property prices [2]. Furthermore, the research subdivided the dataset into territorial clusters, as well as a subset of energy-inefficient buildings constructed between 1946 and 1990, to analyse spatial price variations.

Figure 2 illustrates the evolution of EPC levels from 2014 to 2025 in the considered datasets, highlighting significant shifts in energy performance distribution considering the abovementioned past studies. The most notable trend concerns EPC Level G and Level F. In 2014, Level G accounted for 41.4% of properties, but it dropped significantly to 17.9% in 2017. However, the share of Level G properties increased again to 21.4% in 2021 and 25.9% in 2025. Similarly, Level F increased from 13.3% in 2014 to 20.5% in 2017, declined to 17.5% in 2021, then rose again to 24.2% in 2025. This pattern in the

**Table 1.** Past and current studies on EPC labels on the real estate market of Turin. (Source: Authors' elaboration)

| ID | Authors | Title | Pub Year | Ads Years | Ads Type | N. of records |
|---|---|---|---|---|---|---|
| 01 | Fregonara, E., Rolando, D., Semeraro, P., & Vella, M | The impact of Energy Performance Certificate level on house listing prices. First evidence from Italian real estate | 2014 | 2012 | Listing | 577 |
| 02 | Fregonara, E., Rolando, D., & Semeraro, P | Energy performance certificates in the Turin real estate market | 2017 | 2011–2014 | Listing + Transaction | 1,131 |
| 03 | Barreca, A., Fregonara, E., & Rolando, D | Epc labels and building features: Spatial implications over housing prices | 2021 | 2015–2018 | Listing | 2,092 |
| 04 | Present research | | 2025 | 2022–2023 | Transaction | 5,118 |

lowest classes suggests that while initial progress was made in reducing low-performing properties, the improvements were not sustained over time, partly because the EPC classification criteria were revised in 2015 [41], raising the performance thresholds. Level E followed a similar pattern, rising from 14.6% in 2014 to 22.3% in 2017, with fluctuations leading to 24.6% in 2025. Considering the middle-range classes, Level D initially increased from 18.4% in 2014 to 26.1% in 2017 but gradually decreased to 15.5% in 2025. The share of properties rated with a class equal to A and over remained almost negligible until 2021, when it rose to 0.6%, reaching 3.0% by 2025. This steady increase, though modest, suggests progress in adopting higher efficiency standards, highlighting a positive but still limited shift towards top-tier energy performance. It is noteworthy to mention that in 2021 and 2025, all the A classes (A4, A3, A2, A1, and A) were considered as unique classes for the analysis.

Following the previous research, the analysis presented in this paper is based on a dataset of existing housing units transacted between 2022 and 2023 in Turin (Northern Italy), using data from the TREMO-R GIS. The dataset included 5,118 real estate transaction prices sourced from Immobiliare.it, which one of Italy's leading real estate advertisement websites. Real estate transaction prices in Italy are not publicly available,

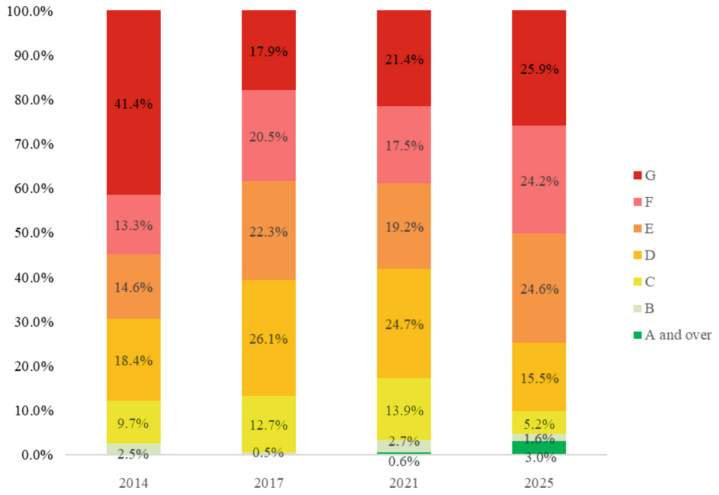


**Fig. 2.** EPC levels distribution during the years (Source: Authors' elaboration on TREMO and TREMO-R data, 2022–2023)

making them difficult to observe. Consequently, researchers, appraisers, and real estate companies frequently rely on listing prices for market analysis and property valuation [19]. As demonstrated in previous academic studies, listing prices play a crucial role in shaping asset value [19], influencing both sales processes and price predictions.

The data sample underwent a cleaning process and outlier removal using the Interquartile Range (IQR) method [21, 44] for each considered timeframe (year 2022 and 2023) by measuring the spread of the middle 50% of the data. The authors applied the IQR method by calculating the difference between the third quartile (Q3) and the first quartile (Q1) to obtain the interquartile range (IQR). Outliers were defined as values falling below Q1 − 1.5 * IQR or above Q3 + 1.5 * IQR. This process is suitable for real estate data cleaning process because it effectively removes extreme values without being influenced by skewed distributions.

Table 2. illustrates the final data sample's summary statistics, including 5,118 total records. The average TLP (Total Transaction Price) in the dataset is €150,093, with a standard deviation of €91,346, indicating a high variability in property prices. The minimum price is €21,000, and the maximum is €870,000. Similarly, the average PVMQ (Transaction Price per Square Meter) is €1,733, with a standard deviation of €567.

The EPC feature is analysed and categorized into three different variables:

- EPC, which examines the EPC labels of the properties individually, ranging from the least efficient class (G = 1) to the most efficient A1-A4 = 7);
- EPC_2021 categorises properties into 3 different levels based on their EPC class: 1 = Lowest efficiency (E-F-G), 2 = Medium-low efficiency (D-C), 3 = Medium-high efficiency (B-A);
- EPC_2025 refines the previous classification by further dividing properties into 4 different levels: 1 = Lowest efficiency (F-G), 2 = Medium-low efficiency (D-E), 3 = Medium-high efficiency (B-C), 4 = Highest efficiency (A1-A4);.

**Table 2.** Data sample summary statistics (Source: Authors' elaboration on TREMO-R data, 2022–2023)

| Variables | Description | Unit | Freq | Average | St. Dev | Min | Median | Max |
|---|---|---|---|---|---|---|---|---|
| *Dependent variables* | | | | | | | | |
| TTP | Total Transaction Price | Euro | 5,118 | 150,093 | 91,346 | 21,000 | 128,000 | 870,000 |
| PVMQ | Transaction Price per square meter | Euro/$m^2$ | 5,118 | 1,733 | 567 | 575 | 1,635 | 3,469 |
| *Independent variables* | | | | | | | | |
| EPC | EPC label (Levels, G = 1, F = 2, E = 3, D = 4, C = 5, B = 6, A4-A3-A2-A1 = 7) | dummy | 1,779 | 2.97 | 1.30 | 1 | 3 | 7 |
| EPC_2021 | EPC label group (Levels, E,F,G = 1, Levels D-C = 2, Levels B-A4 = 3) | dummy | 1,779 | 1.34 | 0.56 | 1 | 1 | 3 |
| EPC_2025 | EPC label group (Levels F-G = 1, Levels D-E = 2, Levels B-C = 3, Levels A4-A3-A2-A1 = 4) | dummy | 1,779 | 1.75 | 0.76 | 1 | 2 | 5 |
| GS | Gross Surface | $m^2$ | 5,118 | 84.13 | 33.13 | 30 | 79 | 300 |
| BOX | Number of garages | dummy | 5,118 | 0.13 | 0.35 | 0 | 0 | 2 |
| ALL | Allocation level | numeric | 5,118 | 6.14 | 2.4 | 0 | 6 | 16 |

(*continued*)

**Table 2.** (*continued*)

| Variables | Description | Unit | Freq | Average | St. Dev | Min | Median | Max |
|---|---|---|---|---|---|---|---|---|
| MTL | Maintenance status level (Levels, 0 = NA; 1 = to renovate, 2 = partially to renovate; 3 = good; 4 = renovated) | dummy | 1,780 | 1.57 | 0.63 | 1 | 1 | 3 |
| CPT | Cadastral Property Type (Levels, Ultra-popular housing = 1, Popular housing = 2, Economic housing = 3, Standard housing = 4, Luxury housing = 5, Villa-style housing = 6) | dummy | 5,118 | 3.13 | 0.58 | 1 | 3 | 7 |
| PT | Property Type (Levels, Economic housing = 1, Apartment = 2, Luxury apartment = 3, Terraced house = 4) | dummy | 5,118 | 1.22 | 0.43 | 1 | 1 | 4 |
| D_YEAR | Deed year | dummy | 5,118 | - | - | - | - | - |

It is important to mention that the EPC class is available for only 1,779 out of 5,118 records, highlighting a 35% completion rate by real estate agents.

## 3 Methods

This study employs two well-established methodologies: Moran's Index[6] and the Spatial Error Model (SEM) [4]. Moran's Index is employed to detect spatial autocorrelation, a phenomenon commonly observed in real estate markets [6, 13, 34]. To complement the statistical results, a LISA (Local Indicators of Spatial Association) Cluster Map is generated, providing a visual representation of Local Moran's I values across all spatial units. The study assumes that when property prices and their features are examined across spatial units, it is crucial to identify both global and local spatial associations between each unit and its neighboring [18, 32, 39, 43].

### 3.1 Local Moran's I and Lisa Cluster Map

Moran's Index [2] is employed to quantify spatial autocorrelation, a widely used measure for detecting spatial dependence. Moran's I is formulated as follows:

$$I = \frac{N}{W} \cdot \frac{\sum_i \sum_j w_{ij}(z_i)(z_j)}{\sum_i z_i^2}$$

where N is the total number of spatial units, $w_{ij}$ are elements of the spatial weight matrix W, which defines the neighborhood structure (with $w_{ii} = 0$ by convention), and $z_i$ and $z_j$ are the standardized values of the variable of interest for spatial units $i$ and $j$, typically computed as deviations from the mean. The term $W = \sum_i \sum_j w_{ij}$ represents the sum of all spatial weights.

Moran's I values range from $-1$ to 1 as follows:

- A positive value (close to 1) indicates positive spatial autocorrelation, meaning that similar values cluster together (high values with high values, low values with low values);
- A negative value (close to -1) suggests negative spatial autocorrelation, where high values are surrounded by low values and vice versa;
- A value near 0 indicates a random spatial distribution, implying no significant spatial dependency.

Building on the results of the Local Moran's I statistic, the LISA Cluster Map serves as a spatial visualization tool that translates statistical outputs into interpretable geographic patterns. While Local Moran's I quantifies the strength and direction of spatial autocorrelation at the local level, the LISA Cluster Map leverages these values—along with their statistical significance—to classify each spatial unit into categories such as high-high, low-low, high-low, or low-high clusters. In this way, Local Moran's I provides the analytical foundation, and the LISA Cluster Map offers an intuitive representation of spatial clusters and outliers, facilitating deeper insights into the spatial structure of the data [3].

### 3.2 Spatial Error Model (SEM)

The linear formulation assumes that observations are independent and identically distributed. However, if significant spatial autocorrelation is detected in residuals, standard

OLS regression may yield biased and inefficient results. To correct this, spatial regression models must be employed. Two primary spatial models are considered: the Spatial Lag Model (SLM) and the Spatial Error Model (SEM). The most appropriate model is selected based on the comparative results of Moran's I and the LM (Lagrange Multiplier) tests.

In this study, price variability exhibits a nonlinear relationship with explanatory variables, and residuals show spatial dependence, necessitating the application of the SEM. The SEM is estimated using the Maximum Likelihood Estimation (MLE) algorithm, which assumes normality in the error term. This model is particularly suitable when measurement errors in locational characteristics exist or when omitted variables are spatially correlated.

Given these conditions, the SEM—also referred to as the Spatial Error Correction Model—is specified as follows:

$$\mathrm{Pi} = \beta_0 + \sum_{k=1}^{K} \beta_k \boldsymbol{X_{ik}} + \boldsymbol{u_i} \text{ with } \boldsymbol{u_i} = \lambda \sum_{j=1}^{N} w_{ij} \boldsymbol{u_j} + \boldsymbol{\xi_i}$$

where $\boldsymbol{u_i}$ is the spatially correlated error term, $\lambda$ is the spatial autoregressive coefficient (to be estimated), and $w_{ij}$ are elements of the spatial weight matrix W indicating the spatial relationship between units $i$ and $j$. The term $\xi$ is a white noise error term with standard properties, namely ($E[\xi_i] = 0$, $Var[\xi_i] = \sigma^2$)

## 4 Results

The TREMO-R research group has been analysing the impact of Energy Performance Certificates (EPCs) on real estate pricing for nearly a decade. Through various econometric models, the researchers have tracked how energy efficiency influences housing market prices, identifying key trends in the city of Turin [7–9, 11, 12, 29]. This extensive research allows a deeper understanding of how sustainability factors integrate into market dynamics over time.

### 4.1 EPC Levels Over Time

Table 3. presents the evolution of the sample size and the presence of EPCs in real estate listings (ADVs) over time. It allows for three levels of interpretation: the type of data used, the statistical representativeness of the sample, and the significance and method of EPC presence analysis.

The data type used has remained consistent over time: real estate listings from the leading online platform. However, while the data from 2011 to 2018 were collected using a stratified random sampling method, in 2025 it was possible to work with the entire set of listings available in 2022–2023 within the municipal area. These 2022–2023 listings were used solely to verify the presence of EPC information in real estate advertisements, while all subsequent analyses in the results section are performed on transaction prices.

Moreover, the shift from listing-based to transaction-based values in 2022–2023 is particularly relevant for understanding whether market expectations regarding energy efficiency align with current buyer behavior.

**Table 3.** Evolution of the presence of EPC labels in ADVs (Source: Authors' elaboration)

| ID | Publishing Year | Ads Years | Ads Type | Total number of ads | Records with EPC label (n) | Records with EPC label on the total 2024 (%) |
|---|---|---|---|---|---|---|
| 01 | 2014 | 2012 | Listing | 577 | 473 | 4% |
| 02 | 2017 | 2011–2014 | Listing + Transaction | 1,131 | 879 | 8% |
| 03 | 2021 | 2015–2018 | Listing | 2,092 | 1,691 | 15% |
| 04 | 2025 | 2022–2023 | Listing | 11,493 | 8,114 | 71% |
| | | | Transaction | 5,118 | 1,779 | 15% |

In 2014 study, 4% of the sample was analyzed, focusing only on listings that included EPC information. Over time, this number has increased and now serves as a proxy for the overall presence of EPCs in real estate advertisements. This growth has been steady, with a relevant increase in the last years.

Finally, an analysis of the average listing prices by EPC cluster in 2022–2023 reveals a price gap of approximately €300/m$^2$ between the "B–C" and the "D–E" clusters, and around €200/m$^2$ between the "D–E" and the "F–G" clusters. A comparison with 2022–2023 data (as shown in Table 4.) indicates that price differentiation by EPC label has become more pronounced over time: while in 2015, the average price of properties in the F–G classes was about 20% lower than those in B–C, by 2023 this gap had increased to 42%. Interestingly, prices for A-class properties appear slightly lower than those for B–C, indicating a trend reversal at the top of the energy rating scale, as shown in Table 4..

**Table 4.** Listing prices (2015–2018), Listing and Transaction prices (2022–2023) for different EPC labels (Authors' elaboration).

| 2015 − 2018 - LP | Frequency | Mean | St. Dev | Min | Max |
|---|---|---|---|---|---|
| A-A4 | 0.004 | 3,295.49 | 1,404.28 | 677.42 | 5,535.71 |
| B-C | 0.1 | 2,997.34 | 1,032.36 | 1,362.73 | 5,588.23 |
| D-E | 0.27 | 2,699.09 | 1,267.38 | 947.37 | 8695.65 |
| F-G | 0.45 | 2,491.28 | 1,088.82 | 916.67 | 7,000.00 |
| 2022–2023 - LP | Frequency | Mean | St. Dev | Min | Max |
| A-A4 | 0.03 | 3,164.46 | 1,256.93 | 583.33 | 7,853.11 |
| B-C | 0.08 | 2,247.34 | 942.46 | 568.63 | 7,710.28 |
| D-E | 0.37 | 1,863.35 | 766.26 | 527.78 | 6,300.81 |
| F-G | 0.52 | 1,712.77 | 835.15 | 503.60 | 7,361.11 |

(*continued*)

**Table 4.** (*continued*)

| 2022–2023 TP | Frequency | Mean | St. Dev | Min | Max |
|---|---|---|---|---|---|
| A-A4 | 0.01 | 2,019.25 | 434.87 | 1,865.50 | 2,173.00 |
| B-C | 0.05 | 2,096.04 | 736.92 | 1,370.50 | 2,916.50 |
| D-E | 0.54 | 1,836.00 | 539.28 | 878.50 | 3,174.00 |
| F-G | 0.40 | 1,478.73 | 492.36 | 633.00 | 2,545.50 |

Over the years, how we've analyzed real estate data to understand whether—and how much— EPCs impact housing prices has also changed. In 2014 and 2017 studies, the analyses primarily relied on standard OLS regression models [42]. Starting in 2021, spatial information was incorporated, restricting the dataset to listings with available geographic data. This methodological shift naturally affected the estimation of the marginal price effect of energy efficiency. Still, even with the more complex spatial models, EPC ratings have continued to play a significant role in shaping listing and transaction prices, as shown in Table 5..

**Table 5.** Marginal prices of EPC labels derived from different regression models and datasets (Authors' elaboration).

| | OLS | OLS | | SEM | SEM |
|---|---|---|---|---|---|
| | 2012 | 2011–2014 | | 2015–2018 | 2022–2023 |
| | LOGLP (Listing Price) | LOGLP (Listing Price) | LOGTP (Transaction Price) | LOGLP (Listing Price) | LOGTP (Transaction Price) |
| | Adjusted $R^2$ = 0,76 | Adjusted $R^2$ = 0,63 | Adjusted $R^2$ = 0,68 | $R^2$ = 0,54 | $R^2$ = 0,44 |
| A (A1-A4) | NP | not significant | not significant | 0,025 | 0,13 |
| B | *(omitted)* | | | | 0,1 |
| C | | | | *(omitted)* | |
| D | −0,06 | *(omitted)* | *(omitted)* | | *(omitted)* |
| E | | not significant | not significant | −0,033 | |
| F | −0,09 | | | | −0,06 |
| G | | | −0,056 | | |

Table 5. presents the marginal price variations associated with different EPC levels over time, derived from regression models applied to different datasets.

A direct comparison across periods is not feasible, as the regression models employed were inconsistent. Notably, the two final models (Spatial Errors Models - SEM) introduced a strong spatial component, capturing localized market dynamics that are not directly comparable to previous specifications.

Despite this methodological shift, some trends are apparent. Analyzing the results derived from the first SEM (2015–2018 dataset of listing prices), EPC categories 'A' and 'B–C' consistently show positive marginal price effects, suggesting that higher energy efficiency has only recently become associated with price premiums. In contrast, the marginal effects for the 'D–E' and 'F–G' categories tend to be negative or close to zero, reinforcing the idea that lower-efficiency dwellings generally have weaker market positioning, even if the magnitude of this effect varies over time.

The results derived from the second SEM (2022–2023 dataset of transaction prices) show a clearer ordering of marginal price values by EPC class, along with an overall increase in the premiums for efficient properties. However, the model's explanatory power ($R^2 = 0.44$) remains modest, indicating that while EPC level plays a role, its impact on price formation may be mediated by other factors in the transaction data.

### 4.2 Local Moran's Index, LISA Map and Spatial Error Model (SEM) results (2022 and 2023 Data)

The Local Indicators of Spatial Association (LISA) clustering analyzes Turin's 2022–2023 real estate transaction prices [2]. This approach helps understand how real estate prices are geographically distributed and whether high or low values tend to concentrate in specific zones (Fig. 3).

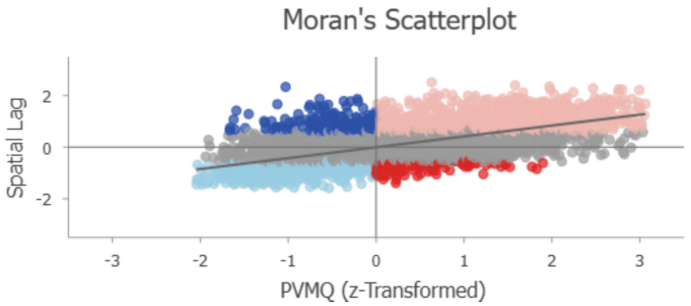


**Fig. 3.** Moran's Index Scatterplot (Source: Authors' elaboration)

Moran's Scatterplot visually represents the global spatial autocorrelation of standardized housing prices (PVMQ, z-transformed). Each dot corresponds to a real estate listing, plotted according to its standardized price (x-axis) and the average standardized price of its spatial neighbors (y-axis). The slope of the regression line is positive, indicating positive spatial autocorrelation: similar price values tend to cluster together. The Moran's I statistic was calculated using a Queen contiguity spatial weights matrix, which accounts for both edge- and corner-sharing neighbors. The analysis was performed in

ArcGIS Pro 3.4 (Esri, 2023) using the *Spatial Autocorrelation (Global Moran's I)* tool, ensuring an accurate assessment of the spatial structure of standardized housing prices.

The R2 value of 0.44 suggests a moderate level of explanatory power—spatial proximity accounts for a significant share of price variability. The four quadrants classify observations:

- Top-right (High-High): high prices in high-price neighborhoods (pink dots);
- Bottom-left (Low-Low): low prices in low-price areas (light blue dots);
- Top-left / Bottom-right: potential outliers or transitional zones.

This result justifies using spatial regression models (e.g., Spatial Lag or Error Models), as the traditional OLS assumption of independence between observations is violated (Fig. 4).

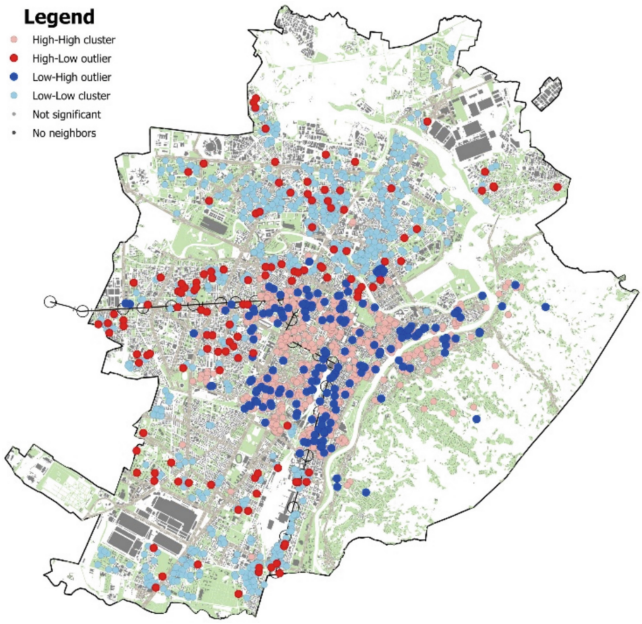


**Fig. 4.** LISA Map (Source: Authors' elaboration)

The accompanying map spatializes the local clusters of standardized property prices based on LISA. The colored dots correspond to the same classification in Moran's Scatterplot, geographically located across the urban territory.

- High-High clusters (pink dots) are concentrated in the central and semi-central areas, confirming the persistence of strong value zones in the urban core;
- Low-Low clusters (light blue dots) are more frequent in peripheral or industrial areas, often aligned with socio-economic disadvantage or lower market attractiveness.

The hexagonal base layer seems to represent a grid or neighborhood aggregation, visually supporting spatial density and trend analysis. Some Low-High (blue) and High-Low (red) points appear along transition corridors—areas where market values are less stable or undergoing transformation. This map adds local granularity to the global insight from the scatterplot, allowing urban planners or housing market analysts to identify areas of interest for intervention, investment, or further investigation.

**Table 6.** SEM model on 2022–2023 TP data (Source: Authors'elaboration)

| SPATIAL ERROR MODEL - MAXIMUM LIKELIHOOD ESTIMATION | | | | |
|---|---|---|---|---|
| **Dependent Variable**: log_PVMQ | | **Number of Observations**: 5118 | | |
| **Mean dependent var**: 7.405149 | | **Number of Variables**: 7 | | |
| **S.D. dependent var**: 0.326569 | | **Degrees of Freedom**: 5111 | | |
| **Lag coeff. (Lambda)**: 0.699809 | | | | |
| **R-squared**: 0.444168 | | **R-squared (BUSE)**: - | | |
| **Sq. Correlation**: - | | **Log likelihood**: -235.027825 | | |
| **Sigma-square**: 0.0592781 | | **Akaike info criterion**: 484.056 | | |
| **S.E of regression**: 0.243471 | | **Schwarz criterion**: 529.839 | | |
| **Variable** | **Coefficient** | **Std. Error** | **z-value** | **Probability** |
| **CONSTANT** | 6,775 | 0,024 | 277,383 | 0,000 |
| **EPC_1** | -0,0618 | 0,010 | -6,309 | 0,000 |
| **EPC_3** | 0,103 | 0,020 | 5,024 | 0,000 |
| **EPC_4** | 0,130 | 0,039 | 3,329 | 0,00087 |
| **building_f** | 0,0107 | 0,0024 | 6,001 | 0,000 |
| **cadastra_1** | 0,000 | 0,000 | 4,789 | 0,000 |
| **cadast_pro** | 0,173 | 0,007 | 25,081 | 0,000 |
| **LAMBDA** | 0,700 | 0,015 | 47,846 | 0,000 |
| **DIAGNOSTICS FOR HETEROSKEDASTICITY RANDOM COEFFICIENTS** | | | | |
| **TEST D VALUE PROB** | | | | |
| **Breusch-Pagan test** 6 166.7584 0.00000 | | | | |
| **DIAGNOSTICS FOR SPATIAL DEPENDENCE** | | | | |
| **SPATIAL ERROR DEPENDENCE FOR WEIGHT MATRIX**: vendita_22_23_log | | | | |
| **TEST DF VALUE PROB** | | | | |
| **Likelihood Ratio Test** 1 1893.0527 0.00000 | | | | |

The SEM model (Table 6.), estimated via Maximum Likelihood on a dataset of over 5,000 observations (log-transformed price per square meter, 2022–2023 data), reports a highly significant spatial error term ($\lambda = 0.6998$, $p < 0.001$). This confirms the presence of spatial autocorrelation in error terms, reinforcing the need to account for unobserved

spatial heterogeneity. The EPC variables reveal a statistically robust and economically meaningful impact on housing prices, even after accounting for spatial effects and other structural and cadastral controls. EPC_1 (reference category likely representing the lowest energy classes, F–G) has a negative and significant coefficient: $\beta = -0.0618$. This indicates that properties in this group are associated with lower log prices, all else being equal. The price penalty can be interpreted as roughly –6.2% in marginal price, signaling an evident market devaluation for energy-inefficient dwellings. EPC_3 (presumably intermediate classes, e.g., C–D) has a positive and significant effect: $\beta = +0.1034$, a strong positive premium of about +10.3%, suggesting that these dwellings are increasingly perceived as market-competitive regarding energy efficiency. EPC_4 (likely high-efficiency classes, e.g., A–B) shows the highest premium $\beta = +0.1309$, A price increase of +13.1%, confirming that high-efficiency homes are rewarded in the marketplace, consistent with growing environmental awareness and regulatory emphasis. These results align with broader empirical evidence indicating a "green premium" for more energy-efficient dwellings and reinforce the idea that energy labels are now a significant component of price formation—especially in urban markets like the one analyzed.

The R2 (0.44) indicates a good level of explanatory power for a cross-sectional housing model, especially considering the inclusion of spatial error terms. Breusch-Pagan test for heteroskedasticity is significant ($p < 0.001$), suggesting the presence of heteroskedasticity—but the SEM still provides consistent estimators under ML. The Likelihood Ratio test for spatial dependence is highly significant ($p < 0.001$), justifying the spatial specification.

This regression provides compelling evidence that EPCs are now embedded into the real estate value system—not just symbolically but with quantifiable effects on listing prices. Even after controlling for spatial dependencies and property characteristics, the strong statistical significance of EPC classes suggests that energy efficiency is not a marginal feature but a central component in how housing markets evolve. This has critical implications for: urban policy (e.g., retrofitting incentives), real estate valuation, and behavioral economics (buyers now react to EPC labels in measurable ways). It also suggests that future models should continue to incorporate both spatial and energy-related variables, especially in cities facing regulatory and environmental transformation.

## 5 Conclusion and Future Insight

The TREMO-R research group has been analysing the impact of EPCs on real estate values since years to contribute to the growing body of research on the relationship between energy performance and housing prices through a spatial econometric lens [10, 19, 20, 27–29]. Leveraging a dataset of over 5,000 property listings in the urban context of Turin during 2022–2023, a Spatial Error Model (SEM) was implemented to account for spatial dependencies that traditional OLS models cannot capture.

The results highlight that EPCs are statistically significant and economically relevant in explaining transaction price variability. Higher energy efficiency ratings (EPC A and B–C) are associated with positive marginal price premiums, whereas lower ratings (EPC F–G) correspond to a negative price impact. These findings confirm the emergence of a

"green premium" and a "brown discount" in the housing market, aligning with broader European evidence.

The spatial diagnostics validate the presence of spatial autocorrelation in both the data and model residuals, justifying the use of spatial error correction. Notably, the spatial structure explains a considerable share of price variation, with the spatial coefficient ($\lambda \approx 0.70$) and $R^2$ values demonstrating a solid model fit. These patterns are further visualized through Moran's scatterplot and local cluster mapping, illustrating how high- and low-efficiency properties are geographically concentrated in specific urban zones. The significance of the spatial error term in the SEM indicates that unobserved spatially structured factors—such as neighborhood amenities, accessibility, or local policies—affect housing prices. This underlines the importance of accounting for spatial autocorrelation to avoid biased coefficient estimates and improve model fit. The spatial correlation also reflects that the housing market is not composed of independent transactions but operates within spatially interconnected sub-markets.

From a policy perspective, the findings suggest that market mechanisms are increasingly internalizing energy efficiency considerations, supporting the role of EPCs not only as informational tools but also as signals of value. This implies that market trends already in motion may reinforce public incentives and regulatory frameworks aiming at building retrofits. Moreover, the significant spatial dependence captured by the SEM implies that interventions in one area may have spillover effects on neighboring zones. For instance, improvements in infrastructure or zoning changes in a specific district could influence property values beyond its administrative boundaries. Policymakers should therefore adopt spatially informed strategies when designing housing or urban development policies, recognizing the interconnectivity across urban space.

Future research could build upon this foundation by incorporating transaction price data, controlling for mortgage conditions, or exploring longitudinal dynamics to assess how EPC premiums evolve over time. Expanding the analysis to other urban contexts may provide comparative insights into how energy efficiency is valued across diverse real estate markets.

In conclusion, this study provides robust evidence that energy performance is currently a salient component in property valuation and that spatially aware econometric models are essential to capture the structure and drivers of urban housing markets accurately. Importantly, these findings have direct implications for the application of the GAR as the EPC serves as a critical instrument in determining the taxonomy-alignment of real estate assets. The observed price premiums for high-efficiency buildings indicate a growing market recognition of sustainability attributes, suggesting that the GAR may further reinforce this dynamic by channeling investment toward greener assets. As financial institutions increasingly integrate GAR considerations into their lending and portfolio decisions, the interplay between regulatory metrics and market valuation is likely to become a powerful driver of transformation within the built environment.

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