

Article

How Does the Presentation of Energy Performance Affect the Price of Houses? A Case Study of Detached Houses in Stockholm, Sweden

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Abstract: Our study aims to analyse whether the capitalisation of a property's energy performance is affected by how it is presented. In place since 2002, there is an EU directive mandating the introduction of an energy performance certificate (EPC) when selling detached houses. This directive was implemented in Sweden in 2009. We analyse how EPC capitalised on housing prices during 2012–2018 for detached houses in Stockholm. This was previously carried out, but our contribution is to analyse both the effect of energy rating or labelling (A–G) and energy consumption (kWh/m²). How energy performance is communicated or displayed to potential buyers conveys that the format, style, and content of energy performance information may influence how buyers perceive its value and impact on the property's market price. We have information on energy rating, consumption, or both for selected properties. This allows us to test the hypothesis that how energy performance is presented affects pricing. We also tested whether information affects different age cohorts differently. The results indicate that how energy performance is presented and visualised is important and that information about rating and consumption might be considered as a substitute for each other. It is also clear that the capitalisation effect differs depending on the age of the building.

Keywords: energy rating; energy performance; labelling; capitalisation; housing prices



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1. Introduction

The energy performance certificate (EPC) was introduced in Sweden on January 1 2009 [1]. EPCs are essential for potential buyers or tenants to accurately assess the building's energy performance and energy consumption costs [2]. Until 2014, providing information on expected energy consumption when selling detached houses was sufficient, and after 2014, both energy rating and energy performance were mandatory (https://energy.ec.europa.eu/topics/energy-efficiency/energy-efficient-buildings/certificates-and-inspections_en, accessed on 9 May 2023).

The use of energy labels to inform consumers about the energy and environmental impacts of products was a topic of interest in recent research [3–7]. Several of them examined the effectiveness of energy labels in attracting consumer attention and increasing the sales proportion of energy-efficient appliances, but not for durable and expensive goods, such as housing. On the other hand, many studies explicitly analyse EPC and its capitalisation in property values, but mainly, energy rating is used in traditional hedonic price models [8–14]. Hence, how energy performance is communicated or displayed to potential buyers might convey that the format, style, and content of energy performance information may influence how buyers perceive its value and the impact on the property's market price.

The research gap we identified concerns, therefore, how energy performance is presented to potential buyers, how potential buyers perceive it, and its capitalisation in housing values. One of the few articles that analysed energy consumption and rating is [13]. They

found consistent results and demonstrated a green premium of 3% on housing list prices in relation to consumption/emissions, with a partial green premium for improvements.

We analyse the research question on capitalising on energy performance based on both consumption and rating in housing transaction prices. Our specific purpose is to analyse whether capitalisation differs depending on whether we present energy performance as an energy class/rating or with information on energy consumption. The identification of the effect is made possible by the fact that the housing price transaction data concerning Stockholm, Sweden enables us to separate which properties were sold with information on energy class or energy consumption, or both.

We use the traditional hedonic method, cohort analysis, and spatial models to mitigate spatial dependence. The traditional hedonic model will be estimated with the help of weighted least squares to ensure that properties with high energy performance are compared with otherwise comparable properties. The weights are propensity score weights. The cohort analysis divides the material into four groups depending on when the property was built. The spatial models refer to Durbin, error, and autoregressive models estimated with maximum likelihood and generalised spatial two-stage least squares.

The hypotheses testing shows that energy consumption measured in kWh per square metre living area is a measure that is more effectively capitalised in housing values than a letter showing energy class. In all models that include energy consumption and energy class, the capitalisation rate for energy consumption is statistically significant, while the energy class is not. However, the capitalisation effect of the expected energy consumption differs when the property is built. The result indicates that energy consumption significantly impacts younger properties more than properties built before 1936 (older than the 25th percentile), having cohort samples of equal size. The spatial models confirm the conclusions.

Our main contribution is to analyse a research question that was not analysed before; namely, the capitalisation of energy performance, depending on how the information is presented. Our unique data material enables us to analyse subsets of real estate transactions where energy performance is presented differently. We also add to the literature by analysing the capitalisation within different construction year cohorts.

The rest of the article is arranged as follows: Section 2 will provide background information on the energy performance certificate within the EU and how it is implemented in Sweden. This is followed by Section 3, which briefly presents the literature on how energy labels influence consumption patterns and behaviour. Section 4 presents the most recent literature on the capitalisation of EPC in house prices. This is followed by Section 5, which presents the selected method. Sections 6 and 7 present the case study, data, and results from the econometric analysis. The article concludes with a discussion of the policy measures in Section 8.

2. Energy Performance Certificate in Europe and Sweden

More information can be found on www.energimyndigheten.se, www.boverket.se/sv/energideklaration/, www.maklarsamfundet.se/fastighetsmaklare-informationsbank/energideklaration, accessed on 9 May 2023.

The energy performance certificate (EPC) was introduced in Sweden on 1 January 2009, for the sale of single-family houses and apartment buildings with a maximum of six apartments. The EPC is a document that displays a building's energy performance and estimates its energy costs. Its purpose is to inform buyers and tenants about a building's energy efficiency, helping them decide which homes are the most cost-effective and environmentally friendly.

The introduction of the EPC in Sweden for the sale of single-family houses and apartment buildings with a maximum of six apartments was part of an EU directive on energy performance in buildings adopted in 2002 [1]. The directive established a time frame for the member states to introduce energy declarations for buildings, and Sweden had a transition period of six years to adapt to the directive and introduce the EPC for single-family houses. Energy experts were trained and certified to issue energy declarations

during this time. It took six years for Sweden to introduce the EPC when selling single-family houses, from adopting the EU directive in 2002 to the Swedish implementation on 1 January 2009.

Energy consumption and rating describe a building's energy performance but can have slightly different meanings depending on the context. Energy performance usually refers to measuring a building's total energy consumption over a given period, including energy use for heating, cooling, lighting, and other technical equipment found in the building. Energy consumption is often measured in kilowatt hours per square metre (kWh/m²) and is used to evaluate how efficiently a building uses energy. The energy rating, introduced in 2014, is a scale that classifies the energy performance of a building. Energy rating scales can vary between countries and regions but often have letter- or colour-coded ratings from A to G, where A stands for the most energy-efficient building and G for the least energy-efficient.

The Housing Authority's regulations and general advice (2007:4 §7a) on energy declarations for buildings state that the building's energy performance classification, from A to G, must be specified as follows: If the building has better energy performance than the requirements set for constructing a new building, range A < 50% of the requirement for constructing a new building and range B > 50% and <75%. Interval C constitutes > 75% and ≤100% of the requirement for constructing a new building. If the building has a worse energy performance than the requirements set for the construction of a new building, the range D > 100% and 135%, range E > 135 % and ≤180%, the range F > 180% and the ≤235%, and range G > 235% [15].

Both energy consumption and energy rating are important for potential buyers or tenants to accurately assess the building's energy performance and energy consumption costs. Therefore, brokers must include both the energy class and the expected energy consumption in the object descriptions according to the rules that apply to energy declarations.

When a broker advertises a property or premises for sale or rent, they must include the energy declaration in the advertisement, as required by law. Energy declaration must also be available to interested buyers or tenants at the exhibition or in other marketing. There are specific requirements for how the energy declaration must be presented in object descriptions. The information on the energy declaration must be clear and easy to understand for the recipient and presented in a standardised way using specific symbols and texts. The information must include energy class, energy use, heating system, and ventilation system.

The EPC in object descriptions has been in place since 2008, but there were some changes in 2014 and 2019. The EPC between 2014 and 2018 shows the energy class on a scale from A to G, but the summary has a different design in the energy declarations made before 2014. One can still see the EPC with the older summary because an EPC is always valid for ten years. The energy classification was introduced in the energy declarations on 1 January 2014, and older energy declarations do not have an energy class. Our case study and data refer to the period 2012–2018, and therefore consist of transactions with different designs of EPC. All have information on energy consumption, but some do not have an energy class. It can refer to properties that were sold before 2014, but also properties that were sold after 2014 but have an older EPC. This enabled us to split the transactions into different samples by whether they have information on both energy performance and energy class, or just energy performance.

Including the object's energy class and expected energy consumption, the description might provide a more comprehensive picture of the building's energy performance and consumption, helping potential buyers or tenants make decisions promoting energy efficiency and reducing environmental impact. Here we aim to test this hypothesis.

3. Research on Energy Labels

The use of energy labels to inform consumers about the energy and environmental impacts of products were a topic of interest in recent research. Several studies examined

the effectiveness of energy labels in attracting consumer attention and increasing the sales proportion of energy-efficient appliances.

For example, [6] examined the effects of the European Union's replacement of its previous A+++ to D labelling scheme for cold appliances with a rescaled A to G labelling scheme on consumers' adoption of top-rated refrigerators. Using a discrete choice experiment on refrigerator adoption among more than 1000 households in Germany, the study finds that showing the rescaled label alone significantly increases consumers' valuation of top-rated refrigerators compared to showing the previous A+++ to D label alone. However, introducing the rescaled label has no benefit when both labels are shown simultaneously.

The effectiveness of the EU energy efficiency (EE) label for appliances in guiding consumers toward more energy-efficient purchases is affected by comprehension issues arising from technical information at the bottom of the label. Monetary information on energy consumption facilitates consumer understanding, but it is technically challenging due to the complexity of the unit of measurement [4]. Although environmental certification schemes, such as the EU energy label, can push people toward energy efficiency, consumers undervalue the energy efficiency of products due to imperfect information and inattention. Providing lifetime cost information increases the willingness to pay for energy efficiency, but the EU energy label alone does not increase demand for energy-efficient products under a control condition [3]. A recent study [5] found that providing 10-year energy cost information labels or QR codes did not increase the average energy efficiency of the appliances sold, and customers' engagement with the QR code was extremely low. The study also found that while treatment increased the importance of energy efficiency in decision-making, this did not translate into increased efficiency of purchased products.

The articles by [16,17] examine the impact of various energy labels and information on the energy efficiency of household appliances. For example, [17] evaluated the impact of the EU energy label and a newly designed monetary lifetime-orientated energy label on private purchases of household appliances. The results indicate that the display of either label increases the proportion of energy-efficient appliances sold, with a greater effect for freezers. The influence of the two labels is similar, except for vacuum cleaners, for which monetary information may have an adverse effect. Furthermore, [16] examine the effectiveness of energy efficiency classes in providing information on the operating costs of durables using energy. By adding simple but accurate yearly or lifetime energy cost information to the European Union energy label for refrigerators, customers purchased lower-priced and lower energy-efficient refrigerators with similar overall energy and total costs. However, this information also increased the search time among buyers, with more attention paid to low-energy-class products. The study concludes that energy classes involve a trade-off between short-term economic savings and higher search costs, and suggests that they may not be adequate in a fair and transparent climate transition.

Ref. [18] discusses using energy labels to inform consumers about the energy and environmental impacts of the products in their study. Results of an eye-tracking experiment on energy labels in the appliance and motor sectors highlight the effectiveness of colour coding and simple grading in attracting consumers' attention. They also identify variations in the recall accuracy of different types of information provided by labels and make recommendations for label design.

Although most studies specifically discuss the impact of adding energy cost information to the European Union energy label for durables that use energy, the findings and insights may have implications for homebuyers. Just as in the case of energy-using durables, energy efficiency is an important consideration when buying a house, as it can impact long-term energy costs and the carbon footprint. However, buyers may face a trade-off between short-term economic savings (such as purchasing a lower-priced, lower energy-efficient house) and the higher search costs associated with finding a more energy-efficient house, especially in a market that can be considered a seller market. Additionally, just as providing energy cost information led to customers purchasing lower-priced and lower-efficiency energy-using durables, providing information about the lifetime energy

costs associated with a house can influence buyers to choose a lower-priced and potentially less energy-efficient option. However, it is essential to note that buying a house involves many more complex factors beyond energy efficiency, and the specific findings and insights from the above articles may not directly translate to this context.

4. Recent Research on EPC and Capitalisation

In recent years, there has been growing interest in the impact of energy efficiency and green certifications on the housing market. Several studies explored this relationship, investigating the extent to which energy efficiency measures and certifications affect housing prices (Selection of published articles: [1,4,8–14,19–33]). Many of these were analysed and presented in literature reviews and meta-analyses, such as [19], and we will focus on the studies published in the last five years.

For example, [20] examined the effect of the Home Energy Rebate programme on the selling prices of single-family residences in the Fairbanks North Star Borough. The study finds that homes that completed the programme sell for a 15.1–16.5% price premium over similar homes that did not, indicating that investments in residential energy efficiency are compensated. The study highlights the importance of efficiency improvements in reducing household energy expenditures in a market with a subarctic climate.

Both [14,21] examine the relationship between green or energy efficiency certifications and housing prices, while [8] investigates the price premium associated with energy-efficient buildings. Ref. [21] finds that green certification positively affects housing prices in Singapore, increasing them by around 3%, with the effect being most substantial for developments with the lowest green rating. Ref. [14] highlights the importance of controlling for potential biases, outliers, spatial dependency, and parameter heterogeneity in estimating the capitalisation effect of energy performance certificates and finds that the certificates are not differently capitalised in the high-end housing price segment but should be more capitalised for house prices in the northern parts of Sweden than in the southern regions.

The study by [8] uses a multicriteria optimisation approach to estimate the price premium for buildings with different energy ratings and finds that higher energy performance is associated with a higher willingness to pay for building units, with price premiums ranging from as high as 55% for A4 to –29% for G compared to D.

Another study suggesting that EPCs play a role in property values is [12]. They investigate the relationship between EPCs and property values in the Belfast metropolitan area and account for spatial effects. The study finds that EPCs have a partial effect on house prices and that there are pricing differences in the spatial variation of EPCs, with pricing effects that are spatial clustering and random.

Ref. [22] investigates the impact of building energy performance and other physical–technical attributes of property prices in Turin’s real estate market. Their results indicate that the EPC labels have an increasing impact on property prices, which differs from previous studies. Moreover, the study highlights the need to consider spatial effects, as the influence of energy attributes varies across different sub-markets. The findings by [23] indicate that EPC positively impacts consumers’ choices, and there is a price premium of over 6% for properties in the best energy efficiency class A compared to the worst class G, all other factors being equal.

However, the findings of [33] suggest that the capitalisation of energy efficiency for the prices of tenant-owned apartments is not significant, with a premium of only 0.8 to 1.2% observed for energy-efficient apartments compared to none-efficient ones. Ref. [9] focuses on the effects of the energy class on the prices in Turin and Barcelona, and shows that applying the same policy led to different impacts on prices. In Turin, the hedonic housing price model estimated an increase given by the EPC of 6.33%, while in Barcelona, the EPC affected property prices by up to 1.88% for each rating level from G to A. However, [31] found, using a sample of 3479 multi-family dwellings in metropolitan Barcelona, that there is a market premium for efficient rated dwellings, with a premium of +7.8%, +3.3% for A, D, respectively, in relation to rating G. These findings suggest that sellers of the best-

rated dwellings are willing to be compensated for a higher amount, all else equal, when selling their assets. Later research suggests a positive relationship between EPC ratings and apartment prices, with a price increase for every EPC rating, but only when location, general architectural attributes, and basic quality attributes are considered. However, when the architectural quality is fully controlled, this correlation disappears. Furthermore, for the upper tier of apartments in central and affluent areas, the EPC rating still affects prices, with a 7.5% increase in price for apartments with A/B/C ratings [32].

These studies and earlier published articles all indicate that green and energy efficiency certifications positively impact property values, although the magnitude of the effect may vary depending on the context, location, and property type. However, controlling for potential biases, spatial effects, and other factors is essential to accurately estimate the capitalisation effect of green and energy efficiency attributes in property prices.

Sections 2 and 3 highlighted the limited understanding of how energy labels and EPC ratings influence consumers' decision-making processes when purchasing energy-efficient homes. While some studies examined the impact of energy labels on consumer behavior, more research is needed to understand how consumers weigh the different factors and trade-offs when making purchasing decisions for homes.

5. Model and Methodology

We will use a combination of methods similar to, e.g., [8,14]. Ref. [14] uses a combination of traditional hedonic modelling, propensity score methods, and spatial hedonic models such as the spatial Durbin model (SDM) to estimate the causal relationship between house prices and energy performance certificates.

On the other hand, [8] use a multicriteria optimisation approach to estimate the price premium for buildings with different energy ratings. The method combines regression models with an optimisation framework to estimate the price premium. They first used a spatial autoregressive model to estimate the price premium, with D as the reference energy rating band. The method involves comparing the predicted price of a building unit with its actual sale price, and the difference is used to estimate the price premium. The study also employs traditional statistical modelling methods, such as multiple regression and hedonic price models, to estimate the price premium and compare the results obtained from these traditional methods with those obtained using the multi-criteria optimisation approach. We will have an equivalent approach but add propensity score weighting [14].

Here, the basic model is a traditional hedonic price model where we estimate the price premium for high-energy performance properties, but we also estimate an SDM [34]. Our focus is not on the modelling approach but on how the same information is perceived differently depending on how it is presented and capitalised into property prices.

Our traditional hedonic model is based on the standard hedonic model, where housing prices (HP) are dependent on the value-affecting attributes (X) of the property, as well as location and neighbourhood characteristics (LN) [35]. To answer the research question, we added information on the energy performance (EP) and energy rating ($topER$) given by the EPC. The variable $topER$ is a binary variable, with the energy class A–C equal to 1 and rating D–G equal to 0. EP is measured in kWh per square metre. Equation (1) illustrates the traditional hedonic model.

$$HP_{it} = \alpha_{i,t} + \beta_j X_{i,t,j} + \gamma_1 EP_{i,t} + \gamma_2 topER_{i,t} + \epsilon_{i,t} \quad (1)$$

where subscript i equals property and t period, and subscript j equals the independent variables. All continuous variables are in natural logarithm form, and parameter estimates can be interpreted as elasticities. We used spatial autoregressive models to address spatial dependency and compared them with traditional hedonic fixed-effects models. Although fixed location effects are included in the hedonic price equation, we deemed this to be an insufficient solution to the problem [36]. Therefore, to identify potential inaccuracies in our findings, we utilised three different models: a spatial error model (SEM), a spatial autoregressive model (SAR), and a spatial Durbin model (SDM).

We used Moran's I after estimating OLS to test the spatial dependence. Ref. [37] found that there is still a lack of standardisation in, especially, mass appraisal models GIS models, with different models using different methods and assumptions. We then applied the log-likelihood ratio test (LR ratio) to compare SDM against SEM and SAR in the next step, following the procedure recommended [38]. The general spatial model can be shown in Equation (2) (e.g., [36,38]).

$$HP_{it} = \alpha_{i,t} + \beta_j X_{i,t,j} + \gamma_1 EP_{i,t} + \gamma_2 topER_{i,t} + \rho W_i HP_{i,t} \quad (2)$$

$$\theta_1 W_i X_{i,t} + \theta_2 W_i EP_{i,t} + \theta_3 W_i topER_{i,t} + \epsilon_{i,t}$$

$$\epsilon_{i,t} = \lambda W_i \epsilon_{i,t} + u_{i,t}$$

The parameter ρ is the estimate of the spatially dependent variable and measures the spatial dependence between transactions. The parameter λ is the estimate in a spatial autoregressive structure for the disturbance and θ is the estimate in spatial lagged independent variables. W is the spatial weight matrix defined as the inverse distance between the observations. OLS estimates of ρ , θ , and λ are biased and inconsistent, and therefore, they must be estimated by, for example, maximising a likelihood (ML) or generalised spatial two-stage least squares [39]. If $\lambda = 0$, then the spatial Durbin model, $\lambda = 0$ and $\theta = 0$, then the spatial autoregressive model (SAR), and $\rho = 0$ and $\theta = 0$, then the spatial error model (SEM).

According to [40] (Bertrand et al., 2004), the standard errors commonly used tend to underestimate the standard deviation of estimators. It is recommended to aggregate standard errors at the cluster level to solve this problem [41]. We cluster-adjust the standard errors by postal code.

To account for variations in good energy performance properties, a propensity score model [42] was used to estimate the probability of a property having an energy rating of A–C or an energy performance below median kWh per square metre. Property variables were used as independent variables in the logistic model, and the resulting probabilities (propensity score) were used to calculate the weights. Properties with good energy performance were assigned a weight of $(1/\text{propensity score})$, while properties with poor energy performance were assigned a weight of $(1/(1-\text{propensity score}))$, suggested by [43]. These weights were then used to estimate the weighted least squares model (WLS) of Equation (1).

6. The Case and Data

The case study we used is the single-family housing market in Stockholm, Sweden. It is a relatively mature housing market where, compared to the housing stock, few new single-family houses were added in recent years. The period we are analysing is characterised by price increases after the financial crisis of 2008. In principle, it was a seller's market throughout the period. The competition for properties for sale was great, and the sales period was short. This undoubtedly meant that value-affecting attributes, such as energy performance, were difficult to price correctly, as it was mainly location and size that influenced the pricing. Throughout the period, energy prices were relatively low compared to today, influencing how energy performance was capitalised.

We use data from Sweden's largest association of real estate agents, namely Svensk Mäklarstatistik AB. Data refer to single-family houses in Stockholm, and we have access to information on the transaction price, contract date, living space, plot area, number of rooms, and year of construction. We have information on energy consumption and classification via the energy declaration in the property descriptions. Some transactions have information on performance and rating, while others only have information on energy consumption, not rating. Furthermore, we have access to latitude and longitude, which allows us to calculate the distance to the central business district (CBD) and the nearest subway station. We used arms-length property transaction data from 2012 to 2018 and divided the data

into four different samples. The different samples are visualised in the Venn diagram in Figure 1.



Figure 1. Venn diagram of the sample.

The first is the default sample, where we would have used the data as we would have used it if we were only using the energy rating as the independent variable measuring energy performance. The data consist of observation with only rating and data with both rating and energy performance measured in kWh. Sample 1 consists of observation with kWh and rating, sample 2 with observation with observation only kWh, and sample 3 with only rating and kWh. The descriptive statistics of samples 1–3 are presented in Table 1.

Table 1. Descriptive statistics in the three different samples.

(a) Descriptive Statistics (sample = with energy performance)					
Variable	Obs	Mean	Std. Dev.	Min	Max
contract price (SEK)	5200	6,376,235.2	2,677,475.4	1,950,000	15,500,000
living area (m ²)	5200	129.098	38.209	58	268
plot area (m ²)	5200	567.749	279.331	119	1505
number of rooms (number)	5200	5.719	1.307	3	10
build year (year)	5182	1954.517	22.817	1877	2016
dist CBD (kilometer)	5200	9.324	3.045	4.115	15.759
dist subway (kilometer)	5200	1.176	0.632	0.152	3.516
<i>topER</i> (A–C class)	5200	0.103	0.304	0	1
<i>EP</i> (kWh)	5200	100.483	42.128	12	289
(b) Descriptive Statistics (sample = with energy rating and energy performance)					
Variable	Obs	Mean	Std. Dev.	Min	Max
contract price	2821	6,984,451.2	2,671,121.4	2,100,000	15,500,000
living area	2821	129.935	37.517	58	267
plot area	2821	574.98	279.454	119	1495
number of rooms	2821	5.799	1.331	3	10
build year	2813	1954.307	23.033	1877	2016
dist CBD	2821	9.141	2.949	4.115	15.759
dist subway	2821	1.162	0.639	0.152	3.516
<i>topER</i>	2821	0.19	0.392	0	1
<i>EP</i>	2821	95.869	40.657	25	287
(c) Descriptive Statistics (sample = only with energy performance)					
Variable	Obs	Mean	Std. Dev.	Min	Max
contract price	2379	5,655,017.3	2,500,595.3	1,950,000	15,500,000
living area	2379	128.107	38.999	58	268
plot area	2379	559.174	279	119	1505
number of rooms	2379	5.624	1.271	3	10
build year	2369	1954.767	22.561	1901	2016
dist CBD	2379	9.541	3.141	4.118	15.752
dist subway	2379	1.193	0.624	0.157	3.507
<i>topER</i>	2379	0	0	0	0
<i>EP</i>	2379	105.953	43.182	12	289

Note. The table shows descriptive statistics on the variables within the three different samples. Sample 1 (Table 1a) includes all observations with an energy performance measure, sample 2 (Table 1b) includes only observations with both energy performance and energy rating, and sample 3 (Table 1c) includes observations with only an energy performance and not an energy rating. The variables are contract price measured in SEK, living area and plot area measured in square metres (m²), number of rooms, building year, distance in kilometers to the central business district (CBD), distance in kilometers to the nearest subway station, *topER*, which is a binary variable for properties with an energy rating of A–C, and *EP*, which is energy performance measured in kilowatt per hour and square metre (kWh). Potential outliers were excluded. All observations above or below the 1 and 99 percentiles were excluded.

The descriptive statistics in Table 1 show that in the data material, we have 2379 observations with only information on energy performance and 2821 with both energy performance and energy rating. In total, we have 5200 observations with information on energy performance. We note that the properties sold with only information on energy performance have an average price of approximately SEK 800,000 lower than all observations. This is even though the property's size and location do not differ significantly from all properties. The exception is that the properties have, on average, higher energy consumption than all properties. This means that properties with both performance and rating information have a higher average price, more have an A–C energy rating and lower estimated energy consumption. This pattern can be explained by the fact that properties

with only information on energy performance were sold earlier than those with information on consumption and rating.

The requirement for a new building is that the *EP* is 100–135 kWh per square metre. Our data show that the average value of *EP* in the three samples is 96–106, i.e., around the requirement for new construction. The share of *topER* in the entire sample is 10%, but in the sample with respect to those with both types of information on energy performance, the share is 19%. However, the correlation between energy performance measures is less problematic than expected, and none of the coefficients are statistically significant. Figure 2 illustrates the distribution of energy classes and the relationship between energy rating and energy consumption.

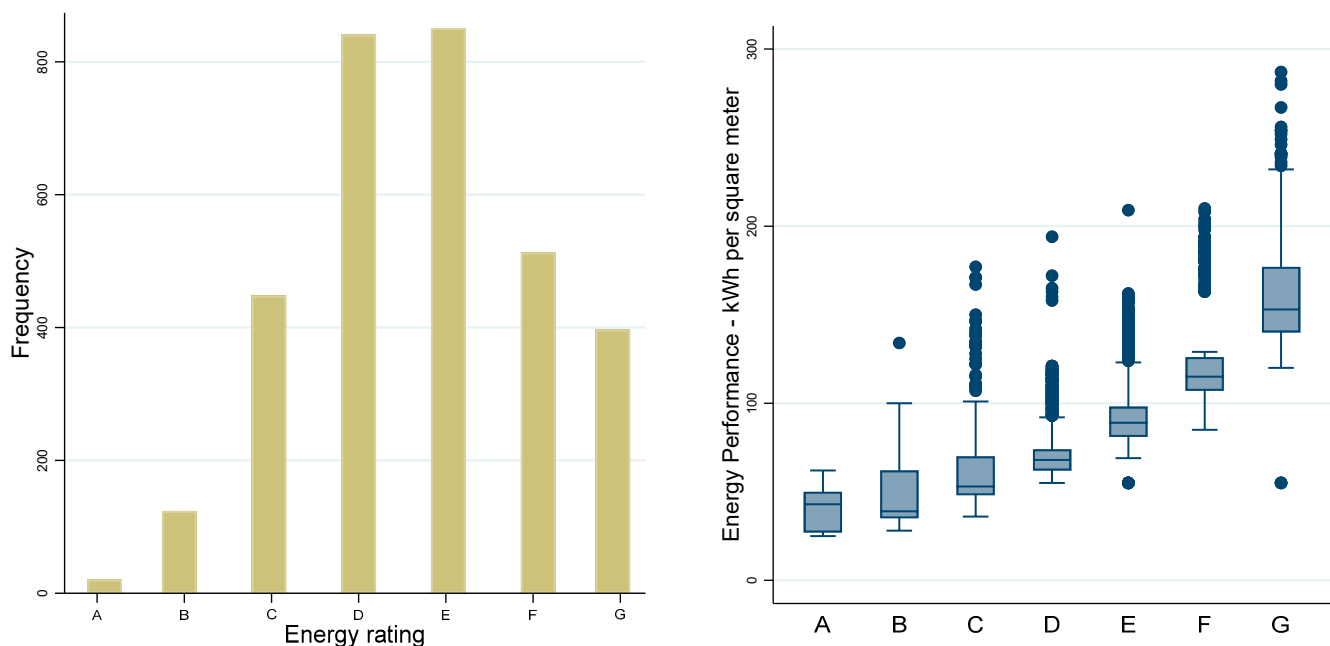


Figure 2. Histogram of energy rating and relation to performance. Note: The plot to the left is the histogram of the energy rating on the x-axis and the frequency on the y-axis. The plot to the right is a box plot between energy rating and energy performance as kWh per square meter. The box plots show the median, quartiles, and outliers. The box in the plot represents the middle 50% of the data, with the bottom of the box being the first quartile, the top of the box being the third quartile, and the line inside the box being the median.

Relatively few properties have an A–C energy rating. Most of the properties have a rating of D and E. The explanation is that most of the properties in Stockholm are older. Relatively few homes were built relative to the housing stock of single-family properties. For older properties, it is less likely that we have a better grade than D. We can also note that relatively many properties have grades F and G; that is, a worse energy performance. These are, above all, older and simpler properties. During the 1930s and 1940s, many detached houses were built in garden towns around Stockholm. These were properties aimed primarily at workers and lower-level officials. Buildings and construction processes were standardised with poorer energy performance by today's standards. We can also see that the energy rating is positively related to the expected energy consumption per square metre. However, the variation within each energy rating is large. Properties in energy classes B and C can have at least as low of an amount of energy consumption as energy class A. Even properties with the lowest energy rating can have expected energy consumption that is on par with properties with ratings B and C. The information on energy performance can be significantly greater than on energy rating.

Figure 3 illustrates the spatial distribution of transactions in Stockholm in 2016. All single-family houses are found in the area around the central parts of the south of the CBD and northwest of the CBD. The colour mark refers to the energy rating the property has. The transactions have an even spatial distribution, and the different energy classes are everywhere. Thus, it is unclear whether there is any spatial clustering of properties with low or high energy ratings.

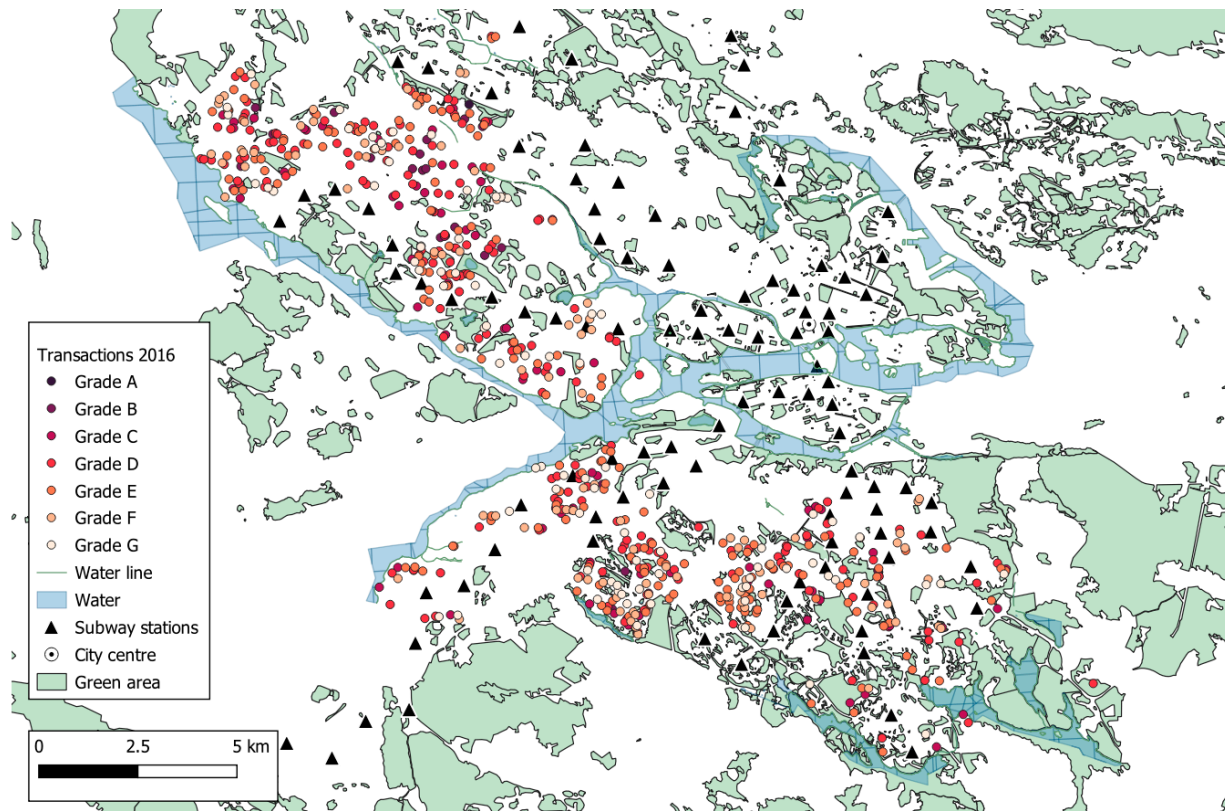


Figure 3. Map of Stockholm and the transactions. Note: The map shows the city of Stockholm and analysed transactions. The map was produced using QGIS, and the city of Stockholm provided the geographic map.

7. Empirical Analysis

The empirical analysis takes place in three stages. First, we will estimate a logistic regression model to calculate the probability that each property has good energy performance (energy class A–C or kWh square metre below the median). With the help of that model, we can calculate the propensity score, which will then be used as propensity weights in the regression models. The results of the model are presented in Table 2. In the second step, we estimate traditional hedonic regression models using weighted least squares (WLS), and the results are presented in Table 3. Finally, we will estimate the spatial hedonic model with maximum likelihood and two-stage least squares. The results of these models will be presented in Table 4.

Table 2. Propensity score model (logistic regression).

	Logistic Regression
Living area	0.0192 (0.20)
Plot area	0.0570 (1.26)
Number of rooms	1.587 *** (12.46)
Building year	8.072 *** (3.42)
Distance to CBD	−0.541 *** (−6.12)
Distance to subway station	−0.0226 (−0.51)
Correctly classified	82.99%

Note. The dependent variable is a binary variable equal to 1 if the property has a grade of A-C or below median energy consumption. The independent variables are living area, plot area, number of rooms, building year, and distance to CBD and subways station. All continuous variables are in natural logarithmic form; *t* statistics in parentheses, *** $p < 0.001$.

Table 3. Traditional hedonic model.

	(1)	(2)	(3)	(4)	(5)
	D1	D2	S1	S2	S3
Living area	0.268 *** (15.48)	0.259 *** (14.87)	0.290 *** (17.18)	0.263 *** (14.74)	0.327 *** (13.17)
Plot area	0.178 *** (12.26)	0.180 *** (12.39)	0.175 *** (16.81)	0.178 *** (12.48)	0.174 *** (15.71)
Number of rooms	0.158 *** (8.19)	0.150 *** (7.89)	0.136 *** (8.92)	0.142 *** (7.46)	0.130 *** (6.06)
Building year	0.269 (0.48)	0.144 (0.26)	0.0840 (0.18)	0.233 (0.42)	0.112 (0.19)
Distance to CBD	−0.366 * (−2.10)	−0.377 * (−2.23)	−0.308 * (−2.15)	−0.361 * (−2.15)	−0.233 (−1.30)
Distance to subway station	0.0450 * (2.12)	0.0455 * (2.17)	0.0476 * (2.37)	0.0503 * (2.44)	0.0472 (1.85)
<i>topER</i>	0.0340 *** (4.71)		−0.00910 (−1.29)	0.00236 (0.30)	0 (.)
Energy rating A		0.0537 (1.58)			
Energy rating B		0.0473 ** (3.16)			
Energy rating C		0.00803 (0.92)			
Energy rating E		−0.0166 * (−2.25)			
Energy rating F		−0.0210 * (−2.25)			
Energy rating G		−0.0598 *** (−5.74)			
EP			−0.0569 *** (−8.29)	−0.0556 *** (−6.68)	−0.0519 *** (−5.79)

Table 3. Cont.

	(1)	(2)	(3)	(4)	(5)
	D1	D2	S1	S2	S3
R^2	0.894	0.896	0.906	0.898	0.909
Adjusted R^2	0.886	0.888	0.902	0.890	0.901
AIC	−3859.1	−3908.9	−6749.3	−3823.3	−3178.1
VIF-value <i>topER</i>	1.14		1.28	1.65	
VIF-value <i>EP</i>			1.42	1.75	1.22
Observations	2882	2882	5152	2794	2358

Note. Default model D1 uses energy rating (binary variable where A-C equals 1, else 0) as an independent variable, and D2 uses binary variables for each rating as independent variables, with energy rating D as a comparison. Model S1 is sample 1, S2 is sample 2, and S3 is sample 3. The variables are contract price measured in SEK, living area and plot area measured in square metres, number of rooms, building year, distance to the central business district (CBD), distance to the nearest subway station, *topER*, which is a binary variable for properties with an energy rating of A-C, and *EP*, which is energy performance measured in kilowatt per hour and square metre (kWh). Continuous variables are in natural logarithm form. Fixed year and location effects are included in all models. Cluster-adjusted standard errors, *t* statistics in parentheses, * $p < 0.05$, ** $p < 0.01$, and *** $p < 0.001$. The variance inflation factor (VIF) is included for the variable *topER* and *EP*.

Table 4. Cohorts analysis.

	(1)	(2)	(3)	(4)
	−1936	1935–1957	1958–1972	1973–
Living area	0.299 *** (12.71)	0.247 *** (7.79)	0.313 *** (9.50)	0.335 *** (6.81)
Plot area	0.111 *** (5.69)	0.122 *** (6.78)	0.164 *** (11.64)	0.179 *** (14.57)
Number of rooms	0.177 *** (6.70)	0.160 *** (5.78)	0.128 *** (4.76)	0.0898 * (2.12)
Building years	−4.013 * (−2.22)	−3.977 (−1.10)	−3.795 (−1.15)	9.732 *** (9.55)
Distance to CBD	0.0102 (0.08)	−0.345 (−1.22)	0.0118 (0.07)	−0.252 (−1.01)
Distance to subway station	0.0436 (1.98)	0.00878 (0.24)	0.0324 (0.63)	0.100* (2.03)
<i>topER</i>	0.00354 (0.23)	−0.0171 (−1.13)	−0.0166 (−1.02)	−0.0104 (−0.66)
<i>EP</i>	−0.0347 ** (−2.93)	−0.0583 *** (−4.89)	−0.0637 *** (−5.03)	−0.0480 * (−2.18)
R^2	0.878	0.872	0.898	0.910
Adjusted R^2	0.865	0.858	0.887	0.900
AIC	−1878.3	−1919.3	−2013.1	−1816.8
Observations	1288	1352	1316	1196

Note. All models are using sample 1. The division of age groups was conducted according to the age distribution's 25th, 50th, and 75th percentile. Column (1) includes properties older than 1936, Column (2) includes properties older than 1935 and younger than 1958, Column (3) includes properties older than 1957 and younger than 1973, and Column (4) 4 includes properties older than 1972. The variables are contract price measured in SEK, living area and plot area measured in square metres, number of rooms, building year, distance to the central business district (CBD), distance to the nearest subway station, *topER*, which is a binary variable for properties with an energy rating of A–C, and *EP*, which is energy performance measured in kilowatt per hour and square metre (kWh). Continuous variables are in natural logarithmic form. Fixed year and location effects are included in all models. Cluster-adjusted standard errors, *t* statistics in parentheses, * $p < 0.05$, ** $p < 0.01$, and *** $p < 0.001$.

Propensity score weighting might be necessary in addition to including the housing and location attributes in the hedonic regression model. We want the properties with high energy performance to be compared to a similar sample of properties with low energy performance to estimate the impact correctly. We ran the *topER* or below-median *EP* as binary variables in a logistic regression where the housing attributes explain good energy performance. The result of the logistic regression presented in Table 2 shows

that the properties' attributes and location can explain which properties have a good energy performance.

Three parameter estimates are statistically significantly different from zero. It is the number of rooms, year of construction, and distance from the CBD. We can note that increasing the number of rooms increases the probability that the property has a good energy performance. The same applies to years of construction, which means that the newer the property, the greater the probability that the property has better energy performance. The latter is an unexpected result. We can also state that the further from the CBD, the lower the probability that the property has a poorer energy performance. Overall, this result shows that comparing properties with good or bad energy performance can be misleading, as we do not know whether the energy performance is realised in house prices or whether it is a new build premium or proximity to the CBD that drives the result. To minimise this problem, we use propensity score weights that, in principle, place more weight on similar observations and include property and location variables together with fixed effects in the hedonic price model.

We used propensity score weights to estimate the traditional hedonic model with WLS. The model's level of explanation is high; around 90% of the price variation (R^2) can be explained by the included variables. Table 3 shows the coefficients and t-values for residential attributes and the distance from the CBD and subway station. In addition to these variables, fixed effects for postal code and year of sale are also included. All continuous variables were transformed into natural logarithms. All VIF-values for the variables *topER* and *EP* indicate that we have a small problem concerning multicollinearity.

In Column (1), the default model D1 ($n = 2895$) is presented, a model used in many studies in which energy performance is measured based on the energy label. In this case, we included a binary variable equal to 1 if the property has energy class A-C, and zero otherwise. The coefficient estimate is interpreted as $e^{0.0343} - 1 = 0.035$ [44]; that is, a property with grade A-C has an expected price premium of 3.5%. Column (2) presents the results of the default model D2. It uses a binary variable for each energy rating with D as the comparison. The results indicate that grades A and C do not have statistically significant estimates, while rating B has a positive estimate. Ratings E, F, and G negatively impact the price compared to energy rating D. The results suggest that a comparable property with an energy rating of G is almost 10% less than a property with a rating of B; that is, higher than the finding of [23]. Model D2 is only marginally better than D1 based on R^2 .

If we compare this result with the model reported in Column (3), we can note that the difference is large. In model S1 ($n = 5172$), we use sample 1, where all observations have information on expected energy consumption in kWh per square metre. Some observations also have information on the energy class. The model has a higher degree of explanation, even if the increase is marginal, from 0.895 to 0.907. The big difference in interpretation lies in interpreting the energy performance capitalisation in the prices. The energy performance measured in kWh has a more substantial and evident effect on the *topER* of the price than the binary variables. Information on expected energy consumption has a higher content of information than the knowledge that the property has an A-C rating.

Model S2 ($n = 2807$) in Column (4) includes only observations with information on energy class and consumption measured in kWh. The degree of explanation is marginally lower compared to the previous model. Here too, we can note that energy performance has the higher explanatory value of *EP* and *topER*, respectively, indicating that expected energy consumption has a higher information content than the binary *topER*. However, we can state that the parameter estimate is positive but not statistically significant. Finally, in model S3 ($n = 2365$), only observations with information on *EP* have the highest degree of explanation. The parameter estimates for *EP* are negative and statistically significant in all models (S1–S3), and the estimates are equivalent. The parameter estimates for *topER* are only statistically significantly different from zero in the model where *EP* is not included.

Parameter estimates from the property attributes are relatively robust, regardless of which sample we analyse. Increased living space by 1% is expected to increase the value

by 0.263–0.332%. This is possibly a relatively low estimate, but also, the number of rooms is included in the specification, so the interpretation is given the number of rooms. If the number of rooms increases by 1%, the price is expected to increase by 0.124–0.155%, all else equal. If the lot size increases, prices are expected to rise. The year of construction is included in the model, but the parameter estimate is not statistically significant, which is somewhat surprising, as it usually shows a high explanatory value in this type of model. Therefore, we also performed the cohort analysis presented below. The distance from the CBD has a negative effect on the price; that is, the farther away from the centre, the lower the prices. However, the distance to a subway station has a positive price impact, which can be interpreted as the proximity to public transport being not essential or as being too close to a subway station having a negative impact due to increased traffic and noise disturbances and crime.

The cohort analysis shows that the traditional hedonic model explains the price variation almost equivalently. The degree of explanation (R^2) amounts to 0.872–0.910. We can note the best explanation for the (4) model, which is the youngest property. One explanation could be that the depreciation did not go as far, and the property's age explains the prices well. The older the properties, the greater the spread when it comes to maintenance and the year of construction, which explains the increasingly poor explanation of the price variation. The variable year of construction is statistically significant for the oldest and youngest properties, but with the opposite sign. The younger the older properties, the lower the price; the older they become, the higher the price. For younger properties, the older they are, the higher the price. Other property attributes have approximately the same price impact as before. Parameter estimates regarding distance to the CBD and subway station are not statistically significant except for one exception: the youngest properties.

Regarding energy consumption (EP), it is still the case that it has better explanatory power than A-C energy classes (*topER*). For the oldest properties, expected energy consumption is less important, and the parameter estimate is only -0.035 for properties older than 1936. Energy consumption significantly impacts older properties, but this does not apply to older properties, where the parameter estimate is somewhat lower.

Table 5 reports the results of the spatial models. It is the same hedonic model as before, with the same dependent and independent variables. The difference is that we included a spatial weight matrix equal to the inverse distance between the observations. We estimated a spatial Durbin model (SDM), a spatial error model (SEM), and a spatial autoregressive model (SAR) maximum likelihood (ML) and generalised spatial two-stage least squares (GS2SLS).

Although we can state that the data show a spatial dependence and the spatial models capture this effectively, it does not significantly affect the interpretation of the impact of energy performance on housing prices. Similarly to the WLS models, energy consumption has a more apparent influence on prices than energy rating. None of the *topER* parameter estimates are statistically significant or independent of spatial models or estimation methods. All estimates of *EP* are statistically significant and negative. Increased expected energy consumption has a negative price impact, all other things being equal. If energy consumption increases by 1%, the price is expected to drop by 0.05–0.07%. A seemingly small impact, but halving the kWh per square metre from 200 to 100, roughly equivalent to going from G to B, results in a price change of around 5%.

We conclude that the estimates of the EPC premium are robust regardless of the presence of spatial dependence and that it is, above all, the energy consumption that impacts the price formation of single-family homes.

Table 5. Spatial hedonic model.

	(1)	(2)	(3)	(4)	(5)	(6)
	Durbin	SAR	SEM	Durbin	SAR	SEM
Living area	0.294 *** (26.46)	0.354 *** (28.06)	0.304 *** (27.63)	0.297 *** (24.97)	0.354 *** (28.01)	0.308 *** (28.21)
Plot area	0.163 *** (26.23)	0.155 *** (26.57)	0.175 *** (31.71)	0.161 *** (25.56)	0.155 *** (26.46)	0.176 *** (32.26)
Number of rooms	0.167 *** (13.11)	0.250 *** (15.50)	0.164 *** (12.88)	0.176 *** (13.00)	0.250 *** (15.52)	0.161 *** (12.66)
Building year	−1.036 *** (−3.81)	−4.997 *** (−16.38)	−1.111 *** (−4.17)	−2.098 *** (−7.60)	−5.009 *** (−15.90)	−1.194 *** (−4.41)
Distance to CBD	−0.584 *** (−18.88)	−0.573 *** (−48.58)	−0.609 *** (−47.05)	−0.610 *** (−23.54)	−0.572 *** (−48.24)	−0.610 *** (−39.39)
Distance to subway station	0.0347 *** (3.37)	−0.0179 ** (−3.17)	0.0104 (1.46)	0.0378 *** (4.04)	−0.0176 ** (−3.12)	0.00999 (1.48)
<i>topER</i>	−0.00519 (−0.65)	−0.0167 (−1.60)	−0.0106 (−1.36)	−0.0125 (−1.48)	−0.0167 (−1.60)	−0.0104 (−1.32)
<i>EP</i>	−0.0553 *** (−9.23)	−0.0722 *** (−9.32)	−0.0582 *** (−9.68)	−0.0598 *** (−9.36)	−0.0723 *** (−9.33)	−0.0578 *** (−9.61)
<i>AIC</i>	−4460.4	−1929.6	−4479.0			
Method	ML	ML	ML	GS2LS	GS2LS	GS2LS
Observations	4950	4950	4950	4950	4950	4950

Note. Table 4 shows the results of the direct effect from the spatial Durbin model (SDM in Columns 1 and 4), spatial autoregressive model (SAR in Columns 2 and 5), and spatial error model (SEM in Columns 3 and 6). The estimates in Columns 1–3 were made with maximum likelihood (ML), and estimates in Columns 4–6 were made with generalised spatial two-stage least squares (GS2LS). All models have fixed year effects and fixed postcode effects in addition to the variables living area, plot area, number of rooms, building year, and distance to CBD and metro station. *t* statistics in parentheses. Continuous variables are in natural logarithmic form. ** $p < 0.01$, and *** $p < 0.001$.

8. Conclusions and Policy Implications

The data material analysed contains 5200 observations on energy performance, with 2379 observations having only information on energy performance and 2821 on both energy consumption and energy rating. Properties with information on energy consumption and rating information have a higher average price and better energy ratings, while properties with only energy performance information have a lower average price and higher energy consumption.

Propensity score weights were used to estimate the traditional hedonic model. The model explains around 90% of the variation in prices. The energy performance measured in kWh has a more substantial and evident effect on housing prices than the binary variable *topER*. This means that when measuring the energy performance of a property, using expected energy consumption in kWh per square meter is more informative in predicting the property's price than using the binary variable *topER*, which only indicates the energy class of the property (A–C). The model results show that the expected energy consumption has a higher content of information than the knowledge that the property has an A–C energy rating and has a more substantial and more evident effect on the property's price. This suggests that buyers and sellers in the housing market pay more attention to the expected energy consumption of a property than just its energy rating. Parameter estimates for property attributes are relatively robust, and increased living space, the number of rooms, and the lot size positively affect the price. The distance to the CBD has a negative effect on the price, while the distance to a subway station has a positive impact. The year of construction does not have a statistically significant impact on property prices. Energy consumption significantly impacts prices in all cohorts, but less so for the old and newest

properties, where the parameter estimate is somewhat lower. For the oldest properties, expected energy consumption is less important.

Moreover, spatial dependence does not significantly impact the interpretation of the relationship between energy performance and housing prices. Energy consumption has a more substantial influence on prices than the energy rating, and the energy rating is not statistically significant, while the energy consumption is statistically significant and negative. This means that an increase in expected energy consumption has a negative impact on housing prices. We conclude that the estimates for the EPC premium are robust, regardless of spatial dependence, and that energy consumption is the primary factor affecting housing prices.

Our conclusions align with those of [8,14], as both have important policy implications for promoting energy efficiency in buildings. Both articles suggest that policymakers can encourage builders and homeowners to adopt energy-efficient building standards. They also highlight the potential financial benefits for property owners and developers who invest in energy-efficient buildings. Incorporating energy-efficient features into building designs can create more attractive properties that command higher prices on the market. However, as did [6], we also conclude that introducing energy rating by itself impacts housing values, but the impact is limited in combination with information about energy consumption.

A potential area of future research could be investigating how changes in energy prices over time can affect the market value of energy performance attributes in the single-family housing market. This could involve analysing data from different periods with varying energy prices and examining how energy performance factors are priced in relation to location and size. Furthermore, future research could explore how the development of new single-family homes in the Stockholm housing market may impact the valuation of energy performance attributes and how this is related to market demand and competition for properties.

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