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RECHERCHE

IS THERE A MARKET VALUE FOR ENERGY PERFORMANCE IN A LOCAL PRIVATE HOUSING MARKET?

Using frontier fonctions instead of the customary hedonistic approach, this article aims to find evidence of a "green value" in a local housing market using notarial data on a small urban area in France.

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Is there a market value for energy performance in a local private housing market? An efficiency analysis approach

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Document de Travail

Résumé en Français

La présente étude tente de déterminer s'il existe une valeur de marché attachée à la performance énergétique des logements résidentiels du parc français privé. Au lieu d'utiliser une régression hédonique usuelle pour modéliser les prix de vente des logements, nous utilisons la méthode des fonctions frontières empruntée à la théorie du producteur. Dans cette perspective de performance, les prix des logements sont déterminés par une combinaison d'inputs, facteurs déterminants dans la vente d'un logement. Cette analyse est en deux étapes. Il s'agit en premier lieu d'estimer une frontière d'efficience, résultat des combinaisons optimales de facteurs, modélisée par la méthode non paramétrique d'enveloppement des données (ou *Data Envelopement Analysis* – DEA). Puis dans un second temps de déterminer si la distance des logements vendus à cette frontière optimale peut être expliquée par des différences de performance énergétique. En utilisant une base de données notariale sur un marché urbain français local et l'information des étiquettes de DPE (Diagnostic de Performance Energétique), nous obtenons une « valeur verte » des logements privés significativement positive quoique faible : entre 1% et 3% du prix des logements vendus. Grâce à une analyse coût/bénéfice des investissements nécessaires pour l'amélioration des performances énergétiques d'un logement privé, nous estimons que cette valeur de marché peut recouvrir entre 4,6% et 5,6% de l'investissement initial.

Key words: Valeur Verte, Performance Energétique des logements, Fonctions Frontières, DEA, Rénovation énergétique, Diagnostic de Performance Energétique

JEL Classification: C5, Q41, Q51, R15, 018

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Is there a market value for energy performance in a local private housing market? An efficiency analysis approach

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Working Paper

Abstract:

This paper aims to find evidence of a "green value" in a local housing market using notarial data on a small urban area in France. We use frontier functions, an original approach that departs from customary hedonistic regressions, to model housing market prices as a production set bordered by an efficiency frontier estimated by Data Envelopment Analysis (DEA). The paper tests if difference in prices (i.e. the distance from the frontier) can be explained by energy performance measured as a normalized categorical ascending kWh/m²/year grade (or Energy Performance Certificate -EPC). We show that there is significative evidence for energy performance's market value. The "Green Property Value" is estimated to range between 1% and 3% of the price for medium-high performance buildings. Our findings are robust to the specifications of the first (frontier estimation) and the second stage (residual analysis). We then propose a cost-benefit analysis to evaluate the return on retrofit investment a household would get from higher market value. We find that housing green property value accounts for a part, between 4.6% in houses and 6.6% in collective dwellings, of the real terms investment in energy retrofit. We interpret our findings with regard to spatial dependencies that affect the market and the heterogeneity between the private and the public social housing stocks.

Key words: Residential Housing Market, Energy Retrofit, Green Value, Efficiency Analysis, Frontier Functions, Data Envelopment Analysis, Energy Performance Certificates

JEL Classification: C5, Q41, Q51, R15, 018

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1. Introduction

To reach European Union's 30% target of energy efficiency gains by 2030 important investments must be made especially regarding the renovation of the private residential sector. A market value for energy performance in private housing can trigger energy retrofits investments. In Europe, buildings account for 40% of total energy consumption and around 75% of them are energy inefficient[1]. In France, the residential sector accounts for 30.2%[2] of final energy consumption and 21% of national GHG emissions. Inefficient[3] buildings in France represent 65% of the total housing stock. The feeble energy performance of the housing stock at the European and at the French level can be explained by two reasons. First, the renovation rate remains very low in European countries. In a recent simulation of the housing stock dynamics, Sandberg et al. (2016) show that the expected renovation rate across all 11 countries was between 0.6–1.6 percent, per year, falling short of the 2.5–3.0 percent expected in many low-carbon transition scenarios. As for France, the renovation rate has been declining both in value and volume by respectively 2.5% and 8.5% between 2011 and 2013. Second, a large proportion of the global retrofit market does not include energy efficiency measures or if they do, they don't always sufficiently improve the building's energy performance. In fact in 2013, only 32% of the retrofit market concerns energy significant improvements. Only 60% of wall retrofits and 45% of roof retrofits integrates energy efficient insulation features (Table 1).

TABLE 1. RETROFIT MARKET IN FRANCE

	2010	2011	2013	2014[4]
Full Housing Stock	33 500 000	33 850 000	34 500 000	35 000 000
Retrofit Market Value and Volume	38.4 bn€/ 6 500 000	38.5 bn€/ 7 700 000	40 bn€/ 9 700 000	35 bn€
Energy Retrofit Market Value/Volume	14 200 M€/ 2 400 000	13 500 M€/ 2 500 000	12 800 M€/ 2 600 000	3 500 000
Average spending per energy retrofitted housing	6 410€	5 330€	5210€	10 000€
Deep energy retrofit Volume and Investment per dwelling	295 000	290 000	265 000	288 000 25 400€

SOURCES : OPEN SURVEYS 2011, 2013, 2015

To meet the EU energy efficiency target, France sets itself the objective to engage in 2017 and onwards in 500 000 yearly building renovations divided into two third for the private housing stock and one third for

[1] Impact Assessment for the amendment of the Energy Performance of Buildings Directive, SWD(2016) 414.

[2] 68Mtoe (or 740 TWh)

[3] Data from ADEME, inefficient buildings are defined as buildings that consume more than 150 kWh/m²/year

[4] OPEN study changed the survey so that it cannot be fully compared to the previous editions. For 2015 edition, no distinction is made between retrofit and energy retrofit market.

social housing stock[5]. According to the data collected by the *Plan Bâtiment Durable*[6] and the OPEN surveys, the renovation targeted rate of 500 000 buildings a year is far reached since 2011 with only 288 000 private buildings retrofitted in 2014 although the social housing market is already achieving a large part of the 2017's goal with 105 000 energy retrofits achieved in 2014. Therefore, the renovation of the existing building stock still lacks major investment from the private sector.

The present work tackles the profitability issue in energy efficiency investment and aims to reveal the presence of a market value for energy performance in the private housing sector. **The objective of this paper is to investigate whether the price difference in statistically similar goods can be explained by energy performance when the information is given by certification labels (EPC).** We want to determine if private housing goods that are certified as energy performant are sold at higher price if so, to compare this additional market with the initial investment needed to achieve that performance.

To answer this question, we have to deal with several conceptual issues that require unlocking three comprehension levels. First, the concept of "green property value" imprints in a broader context of energy efficiency in the housing sector. Second, any attempt to model housing prices must take into account a spatial dimension. Third, the original estimation technique (efficiency frontier estimation) has specific properties specification, evaluation and robustness issues and caveats that need to be assessed within this analytical framework.

The paper is organized as follows; the next section presents a brief review of the literature that studies and quantifies the potential value of energy performance in residential housing. Both efficiency analysis and frontier functions methods are introduced described and discussed in section 3. Data and results are presented in section 4 and we propose a cost-benefit analysis in section 5. The final section eventually displays our conclusions and policy recommendations.

2. Green Property value: definition and objectives

2.1. Green property value as an investment incentive

Green property value corresponds to the additional value generated by a good energy performance. This form of "good will" can be seen as the return on investment of energy efficiency upgrades.

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5 Under the energy transition law ratified in August 2015 that follows the Grenelle 1 law of 2005

6 http://www.planbatimentdurable.fr

There is a broad spectrum of values households can get from making their homes more energy efficient. They come from three perspectives: a consumption-based perspective, a patrimonial-based perspective and a risk hedging perspective. From the first one, homeowners enjoy savings from decreased utility bills and other lower expenses, and get further value from the joy and pride they get from living in a high performance, healthy, and comfortable home. The latter case is a determinant factor for energy efficiency investment. Furthermore, there is a strong potential demand for thermal comfort that an enhanced building performance can provide within a home. In 2013, more than 20% (5.6 million homes) of French households declare that their main residence had roof and/or walls thermal insulation problems, defaulted windows or water infiltration within their walls (INSEE Housing Survey 2013). From the patrimonial prism, investment in the housing quality and energy performance can also be incentivized by the increased rental or selling value, a lower vacancy rate or fiscal benefits. Several studies emphasize that investment decisions in energy efficiency are more often driven by potential rental or property income than energy cost savings (Hyland et al., 2013; Fuerst et al., 2015). Finally, if the buyer expects a rise in future energy related housing costs, she or he can choose a property good that minimizes those risks. For example, if either energy prices increase, a carbon tax is implemented at the residential level, or a bonus/malus system that impacts properties that don't meet minimum efficient standards, then energy efficient houses will be cheaper all other things equal. Good energy performance in housing has intrinsic value thanks to both virtuous carbon footprint and low energy consumption in terms of value and risks. Energy performance certificates (DPE in France) or labels for housing, such as the low-consumption building label (BBC for *Bâtiment Basse Consommation* in France) first reduce the usage cost and trigger fiscal revenue from tax rebates or zero-rate loans. Moreover, they both reduce the risk of implementation of a carbon tax at the national or European level and the risk of increasing energy retail prices and construction thermic standards. Regarding renting market, lower energy charges and more comfort reduces vacancies and default rate from unpaid rents.

What we call the "green property value" is the discounted net present value of both operational and patrimonial value for energy efficiency in homes from a buyer's point of view. As consumers increase their understanding of the connection between energy upgrades and the value of their home, their monthly expenses, and their comfort, they will be more likely to upgrade their homes.

A Green property value can be a difficult piece of information to extract from the market. First, it is unobservable until the transaction process. In other words, for the "energy efficiency" market value to be revealed, the property must be evaluated and priced according to the current market's ability to reveal a "fair price". It can be seen in two ways: either property with good energy performance is sold at higher price on a comparable market or it is sold faster than other comparable properties (reduced vacancy rate). Second, housing specific energy performance requires information that takes time, money and expertise to acquire. Even if energy performance diagnosis is compulsory for the property to be sold in France since 2011, only

39% of the housing stock is displaying valid energy efficiency information (DINAMIC, 2015). On the bright side, information on energy performance of the French housing stock becomes more and more available (only 18% of the housing stock was covered in 2011). Third, property green value must emerge among homogeneous markets: the energy performance must be valuated among goods with similar characteristics. The housing price model and specification are important because endogeneity and correlation in the residuals can create a bias towards or against the revelation of a green property value especially if it is small. Energy performance can be correlated with other general characteristics such as the general state and most of all the age of the property. Last but not least, the value is cannot arise where housing market is facing supply or demand constraints. Therefore energy performance is difficult to estimate in high densities areas like Paris and its suburbs, but also in areas where supply excess demand and prices adjust downwards. That being said, we must bear in mind that our study is imprinted in a peculiar macroeconomic context for the national and regional French housing market. Indeed, the national housing market experienced a double decline of interest rates and selling prices in most regions except for Paris and its suburbs. Bourgogne and its main city Dijon, our area of interest, has not been an exception. Since 2012, housing prices have been falling in the area. Whereas it was relatively stable for new dwellings, the falling in prices has been more abrupt for old dwellings. Individual old dwellings fell by more than 3% a year between 2012 and 2014 (that is our covering period) on average and of around 2% for collective dwelling.

2.2. Green Property Value in the academic literature

A growing body of authors studied the impact of energy efficiency labels on the price of durable goods such as appliances, cars and finally in the residential sector. United States were one of the first countries[7] to develop energy certification labels in the real estate sector. Two labels, Energy Star and Leadership in Energy and Environmental Design labels were created in respectively 1992 and 2000. China and Europe followed suit later with the creation of the European Energy Performance Certificate (hereafter EPC), and the Chinese Green Building Label (CGBL) in 2006 and 2008. Thanks to this seniority, most studies come from the United States that represent a third of the existing literature conducted on the residential sector[8].One third comes from Europe and the last third from Asia continent. Existing studies find on average an increased market value for energy efficient homes of between 3.5% and 4.5% on average for the residential sector (by comparison green property value was estimated on average 13% for the tertiary sector). Appendix 7.1 gives a more detailed analysis of selected literature.

[7] Hong Kong developed the Building Environmental Assessment Method in 1996

[8] We are using the results of the meta-analysis produced for the « *Energies et Territoires* » project in collaboration with LEDI and MSH, university of burgundy. Publication forthcoming (Fizaine, 2017)

In the US, Griffin et al. (2009) used a hedonic model to test the market value for Energy Star and LEED labelled homes in Portland[9]. They found a substantial market premium between 3% and 9.6% of the selling price and a reduction of vacancy rate by 18 days. Later Kahn and Kok (2014) found an incremental value for certified homes in the Californian housing market of 2.1% for the most conservative estimate (that is +$8400 on average). They also underline that the premium offset the input cost for those buildings estimated at $4000-$10 000. In this chapter we also test if green property value in France can compensate part or all of the investment cost in energy efficiency. Our results are showed in the conclusion section.

In Europe, a pioneer study in the residential sector is provided by Brounen and Kok (2011) who analyses the effect of energy labels on housing prices in Netherlands. They found significative discounts and premiums on housing value of -5% to 10%. In 2013, the European Commission and DG Energy established a report of green value estimates for several cities across the EU. They found a price gap from 2% to 11% in market value and from 1% to 5% difference in renting value. All European main cities, except Oxford, carried price-premiums for one-letter improvement in EPC. Authors found an inverse relation with price in Oxford (price discount of 4%) they attributed to the sample size and the dwelling's age omission. Latest studies, like de Ayala et al. (2016), investigate the effect of energy labelling on housing prices using hedonic model with spatial dependences (they used city dummies). They found that ABC homes are priced 9.8% higher than D, E, F or G homes and ABCD labels have a 5.4% premium compared to EFG. In a recent paper, Claudy and Michelsen (2016) focus on the two-way relationship between regional housing market fundamentals, housing quality and residential energy consumption. They argue that energy consumption and motives to invest in energy efficiency measures are not solely derived from energy prices, investment costs, income levels and further socio-economic factors. In fact, regional housing market conditions (vacancy rate, housing price level and anticipated price change etc.) play an important role in the investment decision for more housing quality as properties are not only consumer goods but also and mostly capital assets.

In France, a survey conducted by DINAMIC (2013; 2015) gives quantitative estimations for property green value at the national level but controlled for climatic and spatial differences. DINAMIC studies used both hedonic model and spatial regression analysis to find positive correlation between prices and energy performance ranking according to geographical climate zones, habitable surface, total surface and other qualitative variables such as construction date and number of rooms (integrated as dummies). Depreciations and premiums from average energy rank (D label) range from -15% to 14% depending on climate zones. In 2013, DINAMIC studied the energy performance value using MCO simple regression analysis on a set of housing goods transactions in French province during the years 2010-2011. The report concluded that energy labels had a significant impact on transaction prices. Price difference could make a 30% added value between

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[9] see Walls et al., 2013 for a literature review for the US market

D and A and B labels or a depreciation between D and G labels. Unfortunately, the results suffered from a big uncertainty range because of the lack of energy label coverage and a high correlation with property good' general state and its energy label. The study therefore is concentrated on houses that have a good general state. In 2015, the authors investigate green property value for old dwellings transactions during the years 2012/2013. The study covers 520 000 properties in French province (2/3 of which are individual houses) and 170 000 Parisian and Ile de France housing market (3/4 of which are collective dwellings). Data are from PERVAL (for provincial) and BIEN (Ile de France) notarial databases and cover respectively 55% and 75% of global French transactions. Since the 2011 study, although label repartition is relatively stable in time (A and B labels slightly increased) energy labels coverage has doubled from 20% to 40% and increases the robustness of the analysis.

Studies on the residential sector stress that housing location and dwelling's specificities have potential bias on the valuation for property green value (Kaufman, 2010; Brounen & Kok, 2009; DG Energy, 2011; Bruegge et al., 2016; DINAMIC 2013). First there is a gentrification effect because green certifications are more numerous in city centres. Second because very dense urban zones have specific price and market characteristics, their appeal may create failures on the housing market. The introduction of spatial factors, especially a distance vector to the city centre can control for that aspect. Third, there is a mechanical distinction between newly constructed and old dwellings because the first create automatic green certification when the market is regulated by construction norms as it is the case in France since 1974. Those markets must be therefore analysed separately which is our case as the buildings constructed in 2013 and onwards are identified with the highest rank in their energy performance certification. Fourth, there seems to be a complex relationship between green value and the dwelling's age in some areas. Some would say that it is because there is an unobserved value for old buildings for historical and aesthetic purposes (DG Energy), others argue that it is because green certification improves over time and new buildings create obsolescence on the green value for the second most recent buildings (Bruegge et al., 2016).

3. Methodology

Almost all of the "green property value" literature relies on hedonic regressions. Hedonic models, first described by Rosen (1974) take housing price as the sum of its characteristics vectors. The novelty of this chapter is that we depart from this approach and develop an optimization technique that takes housing price as a performance indicator. We perform a two-step efficiency analysis of the housing price. First we calculate an output-oriented efficiency score that define the housing selling price as combination of several first-order characteristics (surface and localisation). Second we compare each observation and the efficiency score they obtained to the optimal frontier composed by the "best in class" points of the dataset. The distance is as a measure of inefficiency that can determine whether energy performance, along with other qualitative housing characteristics, could explain price inefficiency. That is the price gap between two observations that share the same characteristics, one being closer to the efficiency frontier than the other.

3.1. Efficiency frontier analysis

Measuring productive efficiency, initially called "activity analysis" started in the early 1950s with the pioneering works of Debreu (1951), Koopmans (1951) and Farell (1957). It became a subject of interest in many economic sectors. It first concerned industry and finance businesses that want to optimize their production function in selecting the most productive way to produce the output y with a set of inputs x. The classical formulation of this problem is to consider a vector of inputs $x \in \mathbb{R}_+^p$ producing a vector of output $y \in \mathbb{R}_+^q$. The combination of all input-output pairs such that x can produce y is called the set of production possibilities, P. The comparison of production means (pairs of input x and output y) is made by means of an efficiency frontier, estimated to be the upper boundary of P[10].

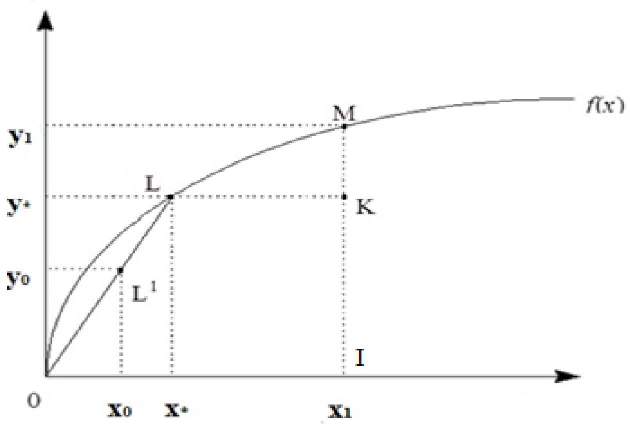
We consider a frontier production function which gives the maximum level of production y from an input x. Thus, for a given amount of x, we could have a level of production lower or equal to:

$$y^b = f(x)$$

By considering the actual production y and the corresponding amount of input x, we derive the productivity of factor x, then its marginal productivity. For comprehensive purpose, we can consider three different combinations of input x and output y are represented on Figure 1. Efficient observations are illustrated by the points L and M from the combinations$(x*, y*), (x1, y1)$. Inefficient observations use either not enough (point L' at$(x0, y0)$) or too much input factors (points I and K) yielding suboptimal output. We consider efficiency as a measure of the distance between those observation points and the frontier.

[10] See Färe (1988). P requires to follow three assumptions 1) P is closed, i.e. It contains its boundary, 2) there is "no free lunches", that is the production requires positive inputs and 3) there is free disposability of inputs and outputs, which is equivalent to say that there is monotonicity of the technology (Simar & Wilson, 2011).

FIGURE 1. FRONTIER FUNCTION ILLUSTRATIVE EXAMPLE



SOURCES: SIMAR (2012)

There are several approaches to model efficiency frontier (Table 2). One can choose to model a deterministic or a stochastic frontier. One also can choose the underlying probability model to be either parametric or non-parametric based on the functional form and the specification of the production set P. Deterministic frontiers are determined as follows:

$$Prob\ \{(x_i; y_i) \in P\} = 1, for\ i = 1, \ldots, n.$$

It means that those models find the estimator that envelops at best the cloud of data points and the distance to the frontier is considered as pure inefficiency. Those models are thus very sensitive to outliers and it is difficult to distinguish inefficiency from noise or random shock to the data. To control for this aspect, we make sure that the dataset we use does not contain such outliers in terms of price and characteristics (price per m^2 or given their distance to focal points).

Stochastic frontiers on the other hand allow data to have random noise that may not be in the production set P and distance to frontier has two components: the noise and the inefficiency. We see that those estimations pose identification problems and need more assumption if we want to further analyse inefficiency. In parametric models, assumption on the probability model, that is the functional form (Cobb-Douglas, Translog…) and the distribution law (Normal, Gamma, Exponential…) of the production frontier, are completely specified. It gives the possibility to use standard estimation methods and easy economic interpretation of the estimators (as elasticities). However it implies that the function describing the production set is known and fully specified. Nonparametric approach makes no such assumption on the probability model of P but economic ones (free disposability, convexity, return to scale, “no free lunches”). It is more robust to model choice and handles more easily multiple input cases (Darario & Simar, 2007).

TABLE 2. FRONTIER FUNCTION INFERENCE TABLE

INFERENCE	**Parametric** : assumptions on frontier function (shape, density, and distance) and Data Generating Process	**Nonparametric :** No analytical assumptions, (only economic)
Deterministic : Finds the estimator that fits the best the cloud of data points Second stage : distance to frontier is pure inefficiency	Analytical model for frontier and DGP F(x,y) Example: estimators COLS, MOLS, MLE + shape of the frontier : Cobb-Douglas, Translog, probability law for u_i	No specific model for frontier or probability law Example : FDH, DEA (convex FDH)
Stochastic : Allows for noise and random shocks Second stage : distance to frontier has two components : noise and inefficiency	Analytical models for frontier and F(x;y) including noise. Examples : OLS, MOLS, COLS, MLE + assumptions on probability law of e_i (noise)	No specific model for frontier and for F(x;y) including noise (some structure of the noise must be applied) Example: SFDH, SDEA

SOURCES: SYNTHESIS TABLE FROM AUTHOR (BASED ON SIMAR, 2012)

We rely on the deterministic, semi-parametric Data Envelopment Analysis (DEA) technique first used by Farrel (1957). These estimators are solutions of a linear program and require free-disposability and convexity as opposition to FDH (Free Disposal Hull) estimators developed by Deprins, Simar & Tulkens (1984) that do not require convexity. We assume that the frontier is determined by the relationships between the “best” extreme observations in terms of combination between input and output. In this optimization problem, we do not assume any scale effect of output (y) depending on the input (x). This means that there is no specific shape of the frontier.

3.2. Apply efficiency frontier estimation to model housing market prices

When applying the efficiency frontier approach to a specific market, one must make sure that the properties of the estimation chosen fit the modelisation features of chosen field in which we implement it. To put it differently, are efficiency frontiers a good analytical and inference tool to model housing prices?

The frontier function approach must take into account spatial correlations in the frontier estimation. To determine the frontier inputs, we rely on the idea that housing price observe a localization rent that is determined by the concentric effect of an urban area on prices and the arbitrage that is made in terms of first based cost : that is the habitable surface. We based this idea on the adaptation on the residential housing market made by (Alonso, 1964) and (Muth, 1969) of the localization rent in agricultural production developed by Van Thünen. The combination (x*,y*) corresponds to the highest sells on the market at that time given their set of inputs. Points that locate under the frontier are said to be inefficient in terms of decision units (output obtained from the combination of surface and localization inputs). To introduce the impact of spatial factors, we include a localization matrix in the efficiency frontier determination. Following Baumont (2004) we use two types of location variables as spatial vectors: the distance to the city centre[11] and the minimum distance to twelve identified districts located in both Dijon city and urban area we will refer further on as “disadvantaged districts” (DD) as they have been selected by their high proportion of social housing and because they are part of an urban rehabilitation policy program. The construction of localisation vectors is further described in the data section.

A choice must then be made regarding the frontier estimation method and the specification that fits best the housing market characteristics. Moreover, when one wants to account for spatial factor in the price model, the best method is to incorporate nonparametric part in the model that allows sufficient flexibility to find substantial spatial variation in house values. Housing economics academic literature most argue in favour of nonparametric or semi-parametric price regressions as they provide more accurate housing price predictions than conventional parametric models (Anglin and Gençay, 1996; Meese and Wallace, 1991). The prediction errors from the semi-parametric model are smaller than those from the parametric models by roughly 10–20% (Bin, 2004). Unlike standard parametric spatial models, this combination of functional form flexibility and spatially varying coefficients helps to reduce spatial autocorrelation without imposing arbitrary contiguity matrices or distributional assumptions on the data (Clapp et al., 2002).

3.3. Measures for price inefficiency in a 2-step approach

Our objective is to investigate whether the price difference can be explained by energy efficiency. In other words, we aim at assessing whether with the same amount of input, housing goods that are energy performant (ranked A, B or C in energy consumption) are sold at higher price. We choose to use both parametric and nonparametric approaches for the frontier function and compare them in the results section.

To model transaction prices in the residential sector, we choose a formalization following Orea, Llorca, and Filippini (2014) of a two-step price setting frontier function:

$$Price = F(S, L, E, X, \gamma)e^{u}$$

Home prices are expressed as a function of independent variables reflecting an arbitrage between surface (S), localisation (L), and qualitative characteristics expressed by discrete variables such as energy performance (E) and other housing main characteristics (X) such as the presence of parking and outdoor facilities, the general

[11] Our data have localization information in the form of Lambert2 coordinates (x,y) that we convert in meter distance, from Dijon city center located “place Darcy”. This center point extracted from google maps in GPS coordinates was then converted in Lambert2 coordinates using the Moran index and the calculator from the website Geofree[11] .

state, the construction period etc. γ is the coefficients' vector associated to the sets of discrete variables (E and X sets) and u is the error term.

If the price setting function is separable in the sense that equation (1) is decomposed into a function f that only reflects the surface/localization arbitrage and a second function h that reassembles the other price features, including energy performance, we have:

$$F = f(S, L)\ h(E, X, \gamma)$$

The two-step approach is chosen as if households show ordered preferences when searching a place to live. The first set of preference reflects the localization (proximity to work and leisure amenities) and budget constraint (expressed by the surface a household can afford given the localisation ideal). The second set of preferences is related to the global quality and services of the housing good and its capacity to satisfy the households comfort needs.

$$Price = F(S, L)e^{u}$$

The semi-parametric part of our approach lies in the hypothesis that the error term is assumed to follow a half normal distribution, ie. $u \sim N^{+}(0, \sigma_u^2)$ (Aigner et al,. 1977). u is a one sided error term capturing the level of underlying inefficiency that can vary over observations and relates to other qualitative dwelling characteristics among them energy efficiency (proxy by a ranking) of the selected home. We can then model the distance to the frontier (inefficiency score) as follows:

$$u = h(E, X, \gamma) + v$$

Where v is a classical symmetric random noise, assumed to be normally distributed: $v \sim N \quad (0, \sigma_u^2)$. Since we assume that both functions are separable, it is possible to observe linear and parametric features for $h(E, X, \gamma)$.

The model estimator and specification of efficiency measures obtained by frontier function is subject to a vivid and growing debate. DEA is a tool that measures efficiency but it does not explain efficiency differentials. To explain inefficiency, that is $1\text{-}\theta \in [0,1]$ on a given set of characteristics Z_i we must control for two main issues : first the separability hypothesis must hold (Simar et Wilson, 2011) and second, the inference at second-stage is applied to a non-standard Data Generating Process hereafter DGP (Simar & Wilson, 2007).

To ensure separability hypothesis we have to verify that there is no dependences between the variables used to perform the efficiency score and the discrete variables used in the residual analysis. We perform independence tests between the variables used in the firs equation and the discrete variables used in the second equation. To perform the second-stage regression analysis, we choose the best fitted regression model between several options: linear regression models such as OLS, censored regression models such as Tobit, fractal regressions models such as Logit, Probit, or regression models that are based on truncated Normal distribution. Given the Data Generating Process of DEA efficiency scores, inefficiency is bounded to the interval [0; 1].

There are various discussions on the relevance and consistency of each method and regression technique used to perform the second step residuals analysis. The debate going on is so contemporaneous that no preferable method has emerged as of today. Hoff (2007) and McDonald (2009) recommend the use of either linear or censored regression, (Papke and Wooldridge., 1996) and (Ramalho et al., 2010) recommend fractal regression models, finally (Simar & Wilson, 2007) propose to use truncated MLE regression with two consecutive bootstrap confidence intervals. (Kneip, Simar, Wilson, 2012) acknowledge also that those problems disappear asymptotically but at a lower rate than $\sqrt{n}$ in classic inference. We know that OLS regression at the second stage is only consistent under specific conditions (Simar & Wilson; 2011). To test the robustness of our results to different specifications, we conduct estimation results using tobit, Normal Truncated and Logit regressions. Once we make sure that confidence intervals and estimators were robust to all regression models and given that we have a big dataset (1588 and 1185 observations), we only display tobit regression output in the results section. We are aware of the limits of tobit censored regression developed by (Simar and Wilson, 2007) that insist on the difference between censored model and truncated models (arguing that the DGP exhibit scores that are not censored by truncated by construction) and we use bootstrap procedures similar to those proposed by Simar and Wilson (2007) to calculate the confidence intervals for tobit estimators to valid inference in this framework. Bootstrapped confidence intervals and standard errors are shown in the result table in appendix 8.2. Note that we used R statistical software to estimate the efficiency frontier functions and Stata13® for the second step regression model.

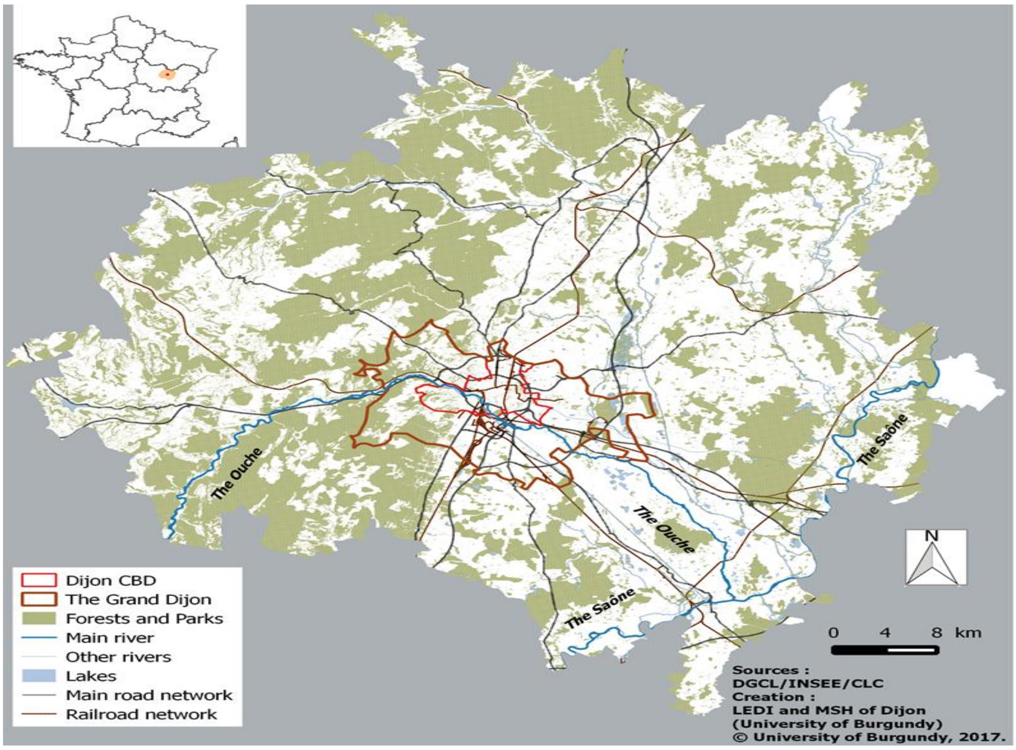
4. Data and results

4.1. Descriptive statistics

Our data come from a notarial base that records residential housing sales in Dijon and its surroundings during the years 2013 and 2014. A reliable, homogeneous local dataset is very important to ensure the market homogeneity and the concentric feature of the land rent theorized by the Muth-Mills model (1972). Dijon urban area is the biggest (of surface and 295 communes) of the region Bourgogne – Franche-Comté (Figure 2) is homogeneous and centred around the historical centre that englobes social, transport and administrative amenities. The global area surface is 3 339 km². It contains 295 commune, 380 236 inhabitants and 168 000 jobs. Its main city Dijon has 153 003 inhabitants. The area is accessible to main urban metropoles: Paris (by train), Lyon (by road), and vallée du Saône. Dijon housing market fundamentals are relatively stable during the year with a "normal" tension according to the French national statistics institute and despite the 2013 price deflation described in section 2. Housing stock is heterogeneous in size, age, price, global quality and localisation relative to its dwelling type (Table 3). Only 2% of sold houses are newly constructed compared to 18% of flats. Individual houses sold on the market are globally older and in worse shape than the collective dwelling market: 50% of houses need refurbishing or renovation against 21% of flats. 88% of individual houses are occupied by landlords and 7% of them have been purchased less than two years ago (INSEE, 2013) whereas 33% of collective flats are occupied by landlords and 70% have been purchased less than two years ago. This shows a clean distinction in the tenure structure, market dynamics and localisation (Figure 3) between the individual and the collective housing markets. As such they will be treated and modelled separately.

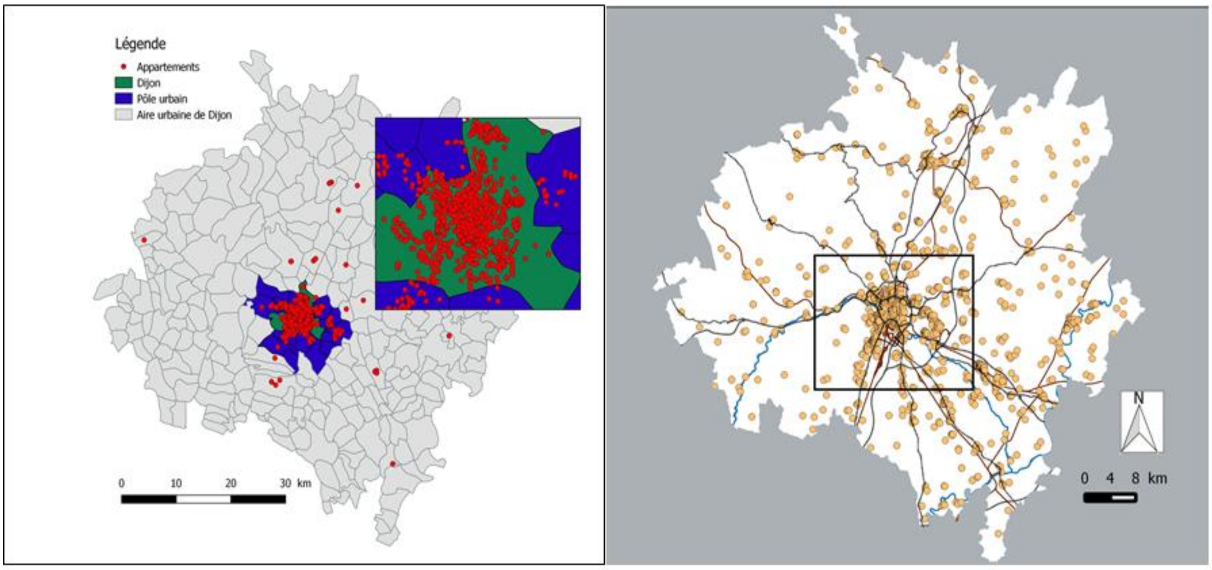
Of the whole dataset (4941 observations in total), we have information on the energy label and its corresponding energy annual consumption for 44% of houses and 34% of flats. There is a small bias regarding the available information and the price. Individual houses that display energy label information have a price 3% higher than the average and on the contrary, collective dwellings that display energy performance certification information have a price 3% lower. We have a final database of 1587 collective dwellings and 1185 individual houses, descriptive statistics are shown in Table 5 and Table 6. Energy Performance repartition matches the national average according to the Phebus survey for the number of ABC dwellings (around1.5% of the housing stock). However, our dataset counts far less inefficient dwellings (F and G labels) than the national average (Table 4).

FIGURE 2. DIJON URBAN AREA IN BOURGOGNE – FRANCHE-COMTÉ



SOURCES: LEDI AND MSH, UNIVERSITY OF BURGUNDY, 2017

FIGURE 3. DATA LOCALISATION POINTS ON DIJON URBAN AREA MAPS



SOURCES: LEDI AND MSH, UNIVERSITY OF BURGUNDY, 2017

TABLE 3. DIJON HOUSING MARKET CHARATERISTICS

	Houses	**Flats**
Construction date	77%	74%
Before 1850 (code A)	2%	1%
1850 / 1913 (B)	6%	2%
1914 / 1947 (C)	22%	8%
1948 / 1969 (D)	19%	19%
1970 / 1980 (E)	18%	18%
1981 / 1991 (F)	9%	10%
1992 / 2000 (G)	7%	8%
2001 / 2010 (H)	13%	11%
2011 / 2020 (I)	4%	25%
Housing state (data coverage 42%)		
Old	98%	82%
New	2%	18%
Housing Type (2) (data coverage 99%)		
Standard 2 rooms apartment		77%
Suburbs pavilion built after 1949 with garden	50%	
City of Village House built before 1949	34%	
Studio Apartment		16%
Duplex or Triplex		7%
Rural House built before 1949	7%	
Villa built recently with high standard commodities	4%	
Other (Farms, mountain houses, Mills…)	4%	
Housing global state at the time of the sale		
Good	49%	79%
To Refurbish	31%	17%
To Renovate	20%	4%

SOURCE: AUTHOR.FROM BIEN DATASET

TABLE 4. ENERGY LABEL REPARTITION

Energy Label	A	B	C	D	E	F	G	Total
Collective dwellings	*0,4%*	*1,1%*	*11,4%*	*33,8%*	*32,4%*	*15,9%*	*5,1%*	*1588*
Individual houses	*0,3%*	*0,7%*	*11,8%*	*31,5%*	*29,3%*	*16,5%*	*10,0%*	*1185*
Total Dataset	0,4%	0,9%	11,6%	32,8%	31,1%	16,1%	7,2%	2773
National share (in 2012)	0,3%	2%	11,7%	24,1%	29,5%	15,4%	15,3%	100%

SOURCE: AUTHOR. FROM BIEN DATASET

NOTES: NATIONAL REPARTITION FROM PHEBUS SURVEY (2013)

TABLE 5. DESCRIPTIVE STATISTICS FOR COLLECTIVE DWELLINGS

Descriptive Statistics for Collective Dwellings	*Average*	*Median*	*SD*	*Minimum*	*Maximum*	*Observation Number*
Collective dwellings (all)	118 734 €	109 174 €	61 399 €	- €	685 000 €	**3543**
Collective dwellings prices energy labelled A-G	116 665 €	105 000 €	61 289 €	3 000 €	685 000 €	**1588**
Collective Dwelling prices not energy labelled	120 450 €	111 830 €	61 448 €	- €	525 000 €	**1954**
Final Database[12]						
Price	**116 737 €**	**105 000 €**	**61 242 €**	**14 000 €**	**685 000 €**	1588
Price m²	2 034 €	2 004 €	677 €	396 €	6 833 €	1588
Surface	59	61	22	8	157	1588
Distance CBD	2409	1641	3025	63	32621	1588
Minimum distance to disadvantaged districts	2197	2141	2176	62	27279	1588
Disadvantaged Districts (D.District Dummy)	0,06	0	0,24	0	1	1588
Parking (ref= no parking)	0,45	0	0,5	0	1	1588
Outdoor (ref=no outdoor)	0,42	0	0,49	0	1	1588
State (1=good)	0,28	0	0,45	0	1	1588
Construction period	0,28	0	0,45	0	1	1588
(Ref= before 1980)						
Energy Grade ABC dummy (Ref=DEFG grade)	0,13	0	0,33	0	1	1588

SOURCES: AUTHORS, DATA PERVAL 2015

[12] Two observations were dropped in the final database for collective dwellings and fourteen for individual houses. We dropped observations if the price ranges outside the 99th percentile (under 46 000€ or over 503 000€ for houses) and if there is a mismatch between the price and the habitable surface (price/m² outlier). Three observations for individual houses do not match the energy label and their state as seen on google earth.

TABLE 6. DESCRIPTIVE STATISTICS FOR INDIVIDUAL HOUSES

Descriptive Statistics for Individual Houses	*Average*	*Median*	*SD*	*Minimum*	*Maximum*	*Observation Number*
Individual Houses (all)	197 301 €	180 000 €	113 133 €	3 000 €	2 500 000 €	**2508**
Individual Houses prices energy labelled A-G	198 551 €	185 000 €	78 790 €	46 000 €	503 400 €	**1199**
Individual Houses prices not energy labelled	193 161 €	176 475 €	127 909 €	3 000 €	2 500 000 €	**1288**
Final Database						
Price	**198 551 €**	**185 000 €**	**78 790 €**	**46 000 €**	**503 400 €**	1185
Price m²	1 815 €	1 750 €	620 €	410 €	5 215 €	1185
Surface	111	106	28	55	225	1185
Distance CBD (meter)	14 045	12 298	10 246	784	42 254	1185
Minimum distance to disadvantaged districts (meter)	10 888	8 636	68 990	127	39 820	1185
Disadvantaged Districts (D.District Dummy)	0,04	0,00	0,19	0	1	1185
Parking (ref= no parking)	0,88	1,00	0,64	0	7	1185
Extrat Bathroom dummy (ref=1)	0,27	0,00	0,45	0	1	1185
State (ref=bad or unknown)	0,30	0	0,46	0	1	1185
Construction period (Ref= before 1980)	0,28	0	0,45	0	1	1185
Energy Grade ABC dummy (Ref=DEFG grade)	0,13	0	0,33	0	1	1185

SOURCES: AUTHORS, DATA PERVAL 2015

4.2. Localisation variables

The distance to the city centre (Place Darcy in Dijon) was calculated using Lambert2 coordinates and corresponding GPS standard coordinates using a software-based conversion formula. From longitude and latitudes data expressed in Lambert2 coordinates in the data base, we calculated the distance from the central point (place Darcy) in Cartesian meter using the following formula:

$$D = \sqrt{(x_{1-}x_2)^2 + (y_{1-}y_2)^2}$$

Following Beaumont (2004), we looked at the distance to the closest Disadvantaged District (or DDistricts). In 2013, DDistricts are identified as sensitive urban zone by the regional council (indicators found on INSEE[13]). They also are neighbourhoods where social housing share is more than 50% of the total stock. We looked for DDistricts in Dijon centre and surroundings using their IRIS number. We then calculated the distance of each sold dwellings to the centre coordinates of the identified districts (Table 7). According to the coordinates, 157 collective dwellings and 112 houses are located in our area of analyse.

TABLE 7. DIJON DISADVANTAGED DISTRICTS

IRIS	District code	GPS Coordinates	City Postcode	City	IRIS Label	Ratio Social Housing /District	Ratio social housing /total
210060000	2105401	47.019517. 4.836603 X: 790023.67 Y: 2227428.30	21054	Beaune	Saint-Jacques	62.4%	65.6%
210120000		47.036587. 4.837740 X: 790049.70 Y: 2229327.59	21054	Beaune	Blanches Fleurs	57.1%	58.5%
210040000	2116601	47.300063. 5.008712 X : 802040.54 Y : 2259027.15	21166	Chenôve	Piscine-Valendons	80.0%	81.1%
210070000			21166	Chenôve	Chapitre-Bibliotheque	62.4%	66.5%
210110000			21166	Chenôve	Petignys-Chaufferie	57.7%	60.2%
210200000			21166	Chenôve	Saint-Exupery	48.0%	49.8%
210210000			21166	Chenôve	Mairie-Stade	47.2%	48.4%
210010000	2123112	47.319822. 5.002421	21231	Dijon	Edouard Belin	98.0%	97.9%

[13] http://www.insee.fr/fr/ppp/bases-de-donnees/donnees-detaillees/duicq/region.asp?reg=26

210020000		X: 801490.59 Y: 2261206.33	21231	Dijon	Le Lac	97.7%	98.1%
		47.317385. 5.003381	21231	Dijon	Fontaines d'Ouche		
210030000		47.333892. 5.067099	21231	Dijon	Gresilles Centre	93.7%	91.4%
210130000	2123118	X : 806279.28 Y : 2262987.62 47.328882. 5.065111	21231	Dijon	Locheres	55.3%	64.6%
210050000	2135501	47.282333 5.058984 805908.29 2257187.71	21355	Longvic	Bief du Moulin	71.3%	72.3%
210080000	2151501	47.315176 5.110125 809645.90 2260971.73	21515	Quetigny	Les Huches	60.8%	63.0%
210140000	2161701	47.339293 4.995940 800927.72 2263353.08	21617	Talant	Belvédère/ Prevert-Plein Ciel	54.6%	61.0%

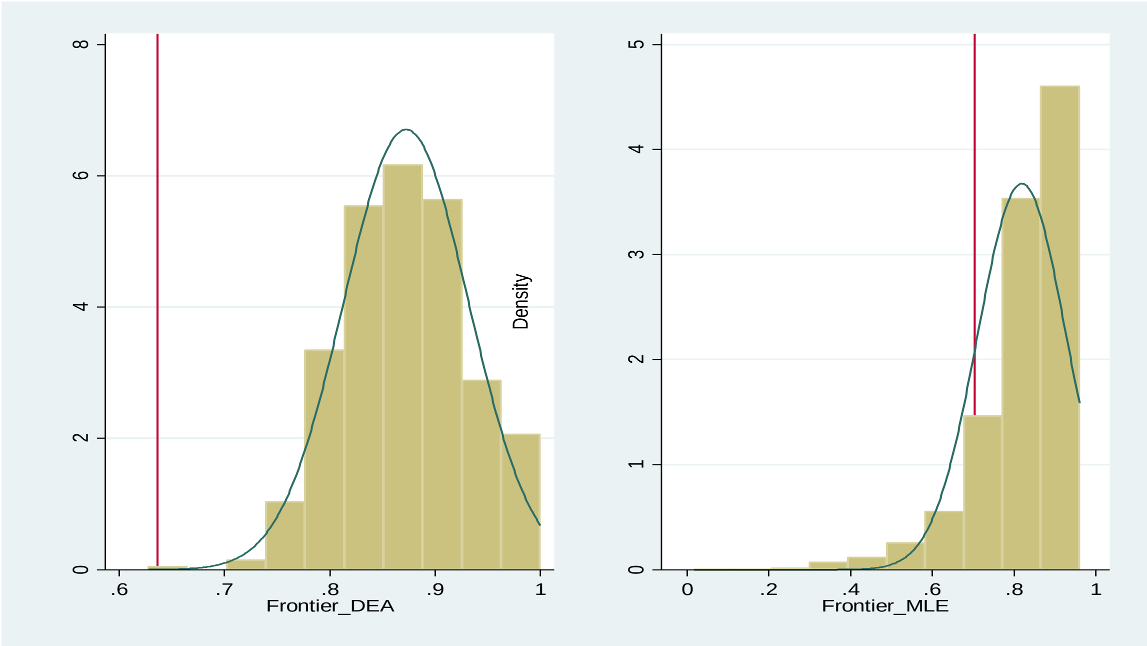
SOURCE: AUTHOR FROM INSEE DATA (RP 2015)

4.3. Results

4.3.1. Stage one: build the efficiency frontier with DEA and MLE analysis with continuous variables.

Frontiers' distribution functions for both DEA and MLE methods are presented in Figure 4. We only rely on the parametric setup to ensure the efficiency frontier verifies the basic economics of the market by looking at the relative signs and amplitude of its parameters. For interpretation and results we rely on DEA frontier as it offers many inference advantages. DEA approach is more robust to model choice and makes no assumption on the probability model and the functional form. DEA production set estimation is closer to the maximum efficiency line (where scores equal 1) that the MLE production set. The latter is also highly skewed due to the estimation method: semi-parametric MLE residuals include the error terms from the interval of the frontier's score and it is therefore more difficult to distinguish between the noise and inefficiency, whereas the DEA estimator doesn't. MLE compares observation to the average fringe whereas DEA compares them to the most efficient unit.

FIGURE 4. HISTOGRAM OF DEA AND MLE FRONTIERS WRT NORMAL DISTRIBUTION



SOURCES: AUTHORS (STATA13® OUTPUT)

TABLE 8. EFFICIENCY FRONTIER COEFFICIENTS AND SIGNIFICANCE TEST

Collective dwellings	X1 : Inverse Distance to city centre	X2 : Distance from the closest disadvantaged districts	X3 : Surface in m²
Beta	0.057	0.099	0.864
SD	0.010	0.012	0.018
T-student	5.909	8.308	47.876

Individual houses	X1 : Inverse Distance to city centre	X2 : Distance from closest DDistricts	X3 : Surface in m²	X4 : Land Surface in m²
Beta	0.210	-0.027	0.777	0.130
SD	0.015	0.012	0.031	0.010
T-Student	13.884	-2.264	25.421	12.939

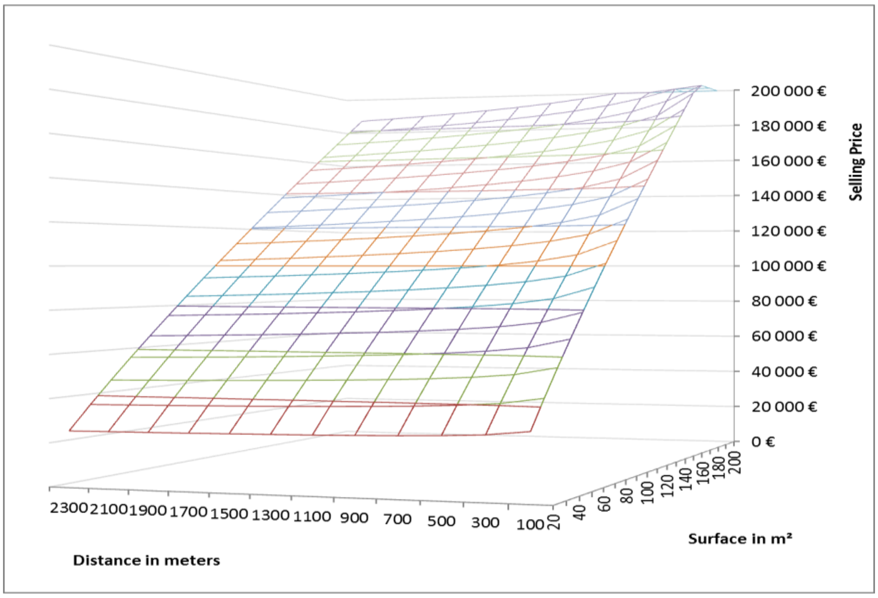
SOURCES: AUTHOR, RESULTS FROM MLE FRONTIER FUNCTIONS' ESTIMATIONS

Table 8 gives us the coefficients associated with the MLE frontier estimation for robustness check of the choice of input. We shall expect the selling price going up the closer we are to Dijon city centre and the further from the neighbour disadvantaged district. In terms of signs, the coefficient of the inverse distance vector should be positive; the closest we are from the city centre (and thus the higher the inverse distance), the higher the price is. Same reasoning holds for the DDistricts minimum distance vector: the further observation points are from the closest disadvantaged district, the higher the price.

The parametric estimation allows us to check that the collective dwelling market is positively impacted by the distance there exists between a specific housing good and its most neighbour disadvantaged district. However, we do not significantly observe this correlation for individual houses. The explanation can be that first, the disadvantaged districts are mostly composed of collective dwellings and their effect on price may only be seen on similar goods i.e. collective buildings and second, because those districts are mostly concentrated in the centre whereas the individual houses' market is much wider spread. Individual houses seem to suffer more than collective dwellings from being remote. The coefficient associated to the distance vector to the city centre is 4 times higher for individual houses than for collective dwellings. That is often the case in French urban configuration where all the activity is centralized downtown (jobs, shopping, culture, administration). The latter being mostly composed of collective buildings, it may explain why the distance effect is less important there (because they are all on average closer to city centre that individual houses).

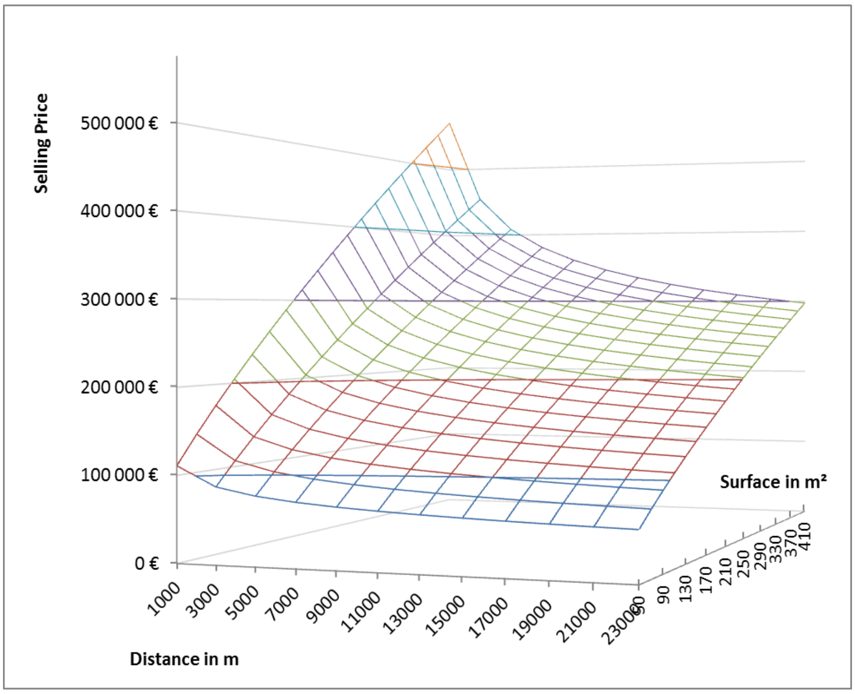
The following figures (Figure 5 and Figure 6) give a visual estimation of the efficiency frontier in the collective and individual market based on the MLE estimates for the impact on prices of the habitable surface and the distance in meters to Dijon's city centre.

FIGURE 5. COLLECTIVE DWELLINGS PRICES SET ESTIMATED USING MLE FRONTIER ESTIMATES



SOURCES: AUTHOR

FIGURE 6. INDIVIDUAL HOUSE PRICES SET ESTIMATED SET USING MLE FRONTIER ESTIMATES



SOURCES: AUTHOR

4.3.2. Stage 2: Frontiers' residual analysis

In a second step, we want to determine if inefficiency (residuals from the efficiency frontier) can be explained by housing characteristics and if among them, energy efficiency has any impact on the value of residential housing price. Table 9 and Table 10 show the results for individual houses and collective dwellings. We would expect that the energy label has a negative impact on the frontier's residuals, i.e. that ABC labelled dwellings are located closer to the efficiency frontier than DEFG homes. We use tobit censored model to estimate the impact of housing qualitative characteristics on efficiency score's residuals in levels.

TABLE 9. RESULTS FOR INDIVIDUAL HOUSES

TOBIT regression for frontier's residuals in levels censored to [0;1]	DEA residuals	MLE residuals
Energy efficiency Grade ABC	-0.0107***	-0.0303***
	(0.00295)	(0.00956)
Number of Rooms	0.0207***	0.00384*
	(0.000666)	(0.00197)
General State	-0.00444**	ns
(ref=bad or unknown)	(0.00213)	

Pool	-0.0206***	-0.0515***
	(0.00458)	(0.0142)
Construction period		-0.0594***
(ref= before1975)		(0.00697)
Parking	ns	-0.0152**
		(0.00695)
Constant	-0.182***	
	(0.00949)	
Sigma	0.0329***	0.103***
	(0.000698)	(0.00211)
Observations	1,185	1,185

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

SOURCES : AUTHORS

TABLE 10. RESULTS IN REDUCED FORM FOR COLLECTIVE DWELLINGS

TOBIT regression for frontier's residuals in levels censored to [0;1]	DEA residuals	MLE residuals
Energy efficiency Grade ABC	-0.0122***	-0.0139*
	(0.00326)	(0.00759)
Number of Rooms	0.0241***	0.0146***
	(0.000976)	(0.00227)
Extra Bathroom	-0.0444***	-0.0607***
	(0.00600)	(0.0140)
General State		-0.0103*
(ref=bad or unknown)		(0.00551)
Construction period	-0.00612**	-0.0366***
(ref= before1975)	(0.00288)	(0.00675)
Parking	-0.0132***	-0.0402***
	(0.00247)	(0.00577)
Outdoor	-0.0150***	-0.0418***
	(0.00246)	(0.00574)
Constant	0.0373***	0.107***

	(0.00963)	(0.0225)
Sigma	0.0420***	0.0978***
	(0.000752)	(0.00174)
Observations	1,588	1,588

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

SOURCES : AUTHOR FROM SECOND STEP RESIDUALS REGRESSION ANALYSIS

As we see on Table 9 and Table 10, ABC rated homes reduce price inefficiency in individual houses by [1.07%; 3.03%], and [1.22%; 1.39%] in collective housing. The magnitude of the green property value depends on the frontier estimation method. DEA estimator gives more conservative measures. In individual houses, buyers seem to (sadly) value more the presence of a pool than energy performance (price improves by 2% and 5%), but value less the number of rooms which can translate the preference of the actual market for big living areas rather than a lot of small and less luminous rooms for the same habitable surface.

It is interesting to note that some explanatory variables are significative when the frontier is calibrated using MLE, while it is not the case when we model the efficiency frontier with DEA. For instance, the impacts of general state of the housing good, parking and bathrooms; as well as the construction period, are sensitive to the method used. In fact, it appears that the variance associated with MLE residuals is much higher than the one estimated with DEA frontier estimation because of the inclusion of extreme values within the DEA production set whereas they are left in the residuals of the MLE frontier estimation. We tested for the robustness of the DEA coefficient for both dwelling types using bootstrap intervals for coefficient and standard errors (see appendix 8.2).

Using the same models, we derived the green property value as a discount applied to inefficient homes. Output results are displayed in appendix 8.3 but Table 11 gives a synthesis of the results. We see that the less energy performant a housing good is, the higher the discount on price compared to a performant property good. D and E labels are more sanctioned in collective dwellings that in individual houses. The discount associated to the G label remain the same by dwelling type when using DEA but reach 12% in individual houses (comparatively to 2.7% in flats) when using MLE.

TABLE 11. GREEN PROPERTY DISCOUNT FOR INEFFICIENCT HOMES

	Individual Houses		Collective dwellings	
	DEA	MLE	DEA	MLE
ABC	ref.	ref.	ref.	ref.

D	-1,02%	-1,90%	-1,20%	Non significative
E	-1,08%	-3,80%		
F	-1,10%	-6,20%	-1,30%	-2,70%
G	-1,30%	-12%		

SOURCE: AUTHOR FROM TOBIT REGRESSION'S RESULTS ON THE FULL DPE LABEL VARIABLE

5. Cost-benefit analysis and discussion

Is Green Property Value an effective tool to reduce the energy efficiency gap? We just demonstrated that high energy performance certification (A, B or C label) can have a market value on the private housing market. Although it is a robust result, this value is rather small compared to the upfront investment needed to obtain the corresponding certification in the retrofit market, especially in the existing housing stock. In this section we provide a simple cost/benefits analysis to measure to what extend the green property premium at the time of sale can offset part of the upfront cost needed to achieve significant energy retrofits.

Green building labels are already costly to obtain. (Dwaikat and Ali, 2016) show that, according to the academic and professional literature, green buildings can cost up to 21% higher than regular construction[14]. Such analysis doesn't exist for the upfront cost estimation in energy retrofit for the existing stock. We used empirical studies and case experiments in France conducted by either academics, dedicated public institutions (ADEME), social housing corporations (*Union Sociale de l'Habitat* or USH) and energy suppliers[15] (EDF) to propose a first estimation of the investment needed to achieve significant energy retrofit for existing housing goods.

As shown in Table 12, for two types of retrofit investments in dwellings in Dijon area, investment return from green property value for an average flat (house) priced 2030€ (1815€) per m² and sized on average 60m² should be around 18€ and 24.5€ (54€-28€) per m² relatively to the frontier method used (higher green property values are recorded for MLE frontier estimation). Upfront costs per m² are obtained from the average of the existing studies and experiences in energy retrofit per dwelling type corresponding to the attribution of a grade B in the EPC (more detailed explanation on cost estimations are shown in appendix 0). Green property value offers a return on gross initial investment between 5% and 14% in individual houses and 6%-7% in collective dwellings.

14 Among the 17 reviewed empirical studies of the paper, only six publications were classified as academic publications,

15 The French electricity provider EDF performed an experimental trial on selected houses to abide by its obligation to obtained Energy Performance Certificates in 2014.

TABLE 12. COST BENEFIT ANALYSIS

	Average Price per m²	Average surface	Average energy retrofit investment / m²	Green property Value per m²	Investment return
Houses	1815 €	110	391 €	18€-54€	5% -14%
Flats	2030 €	60	398 €	24.5€-28 €	6%-7%

SOURCES: UPFRONT COST PER M² ARE OBTAINED BY COMPILING EXISTING REAL CASES STUDIES (SEE APPENDIX 0)

This result doesn't take into account the impact on the investment decision of other determinants, either monetary (liquidity constraints and interest rates levels) and non-monetary such as comfort which is the most invoked reason to engage in energy retrofit among households (OPEN, 2015). People invest to improve the quality of their home mostly to improve their comfort, then to reduce their utility bill and finally to improve the patrimonial value of their home.

Can those results be extended to the national level? Green Property Value is deeply rooted with market fundamentals: household's income, property tax levels, interest rates, vacancy rate and expected price changes. Those fundamentals are heterogeneous and vary across regions and cities. They influence energy performance in two ways: from the supply point of view and from the demand point of view. A market where supply excess demand sets poor expectations about price change dynamics and offers low incentives to invest in housing quality. Especially low income levels, risky environment and high vacancy rate can lower investment per square meter (Claudy and Michelsen, 2016). On the other hand, when demand excess supplies on a local market, housing goods are valued most for their localization features. A fair green property value is more likely to emerge in local housing market with sound fundamentals (with no shortage or excess in production). To our viewpoint, green property value investigation should be continued at the disaggregated local or regional level rather than investigated at the aggregated national level.

6. Conclusion

This chapter uses the efficiency frontier two-stage analysis to model price efficiencies in the local housing market of Dijon (Burgundy, France). Controlling for both distance and contiguity spatial factors, we provide empirical proof of the existence of a green property value. We find that, given other qualitative characteristics (parking, construction period, pool…) individual houses bear a green premium between 1% and 3% and 1.2% for collective dwellings. Magnitude of green property value varies across the frontier's estimation method. The DEA estimator gives more conservative estimates than the Maximum Likelihood Estimator.

We acknowledge that our green value estimates fall on the most conservative range of the green property value literature (1% to 3% with respect to 3.5%- 4.5%). It might be the fact that the introduction of spatial factors, especially distance vector can underestimate the green property value. Meta-analysis showed that distance vectors tend to reduce significantly the estimated green property value (Fizaine et al., 2017). Whereas the introduction of precise geolocalization features tends to lead to higher green property value estimates (Maslianskaia-Pautrel, 2016). The calibration of a spatial model within the efficiency frontier analysis framework should be in that sense, further investigated[16].

After a simple cost-benefit analysis, we show that green property value can offset the gross retrofit upfront cost from 5% to 14% in individual houses and from 6%-7% in collective dwellings. Combined with a better monetary valuation for comfort utility, the diffusion of public information about the existing green property value, associated with repeated test measures to check market fundamentals on a local level, can trigger private investment in energy efficiency and address part of the profitability issue raised in the energy efficiency gap literature.

[16] We can cite the work of (Fusco and Vidoli 2015) that develops a statistical tool to estimate spatial stochastic frontier functions to model firm performance in Italy with regional heterogeneity effects.

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8. Appendices

8.1. Literature Review for green housing value

Study Reference	Data Coverage	Method	Results
USA			
Griffin et al., 2009	EnergyStar labels in Portland	Hedonic model using dummy for Energy star or LEED criteria	Market value : +3%/+9,6% Vacancy rate (sell duration) ; -18 days
Kahn and Kok (2014)	Green labels in the California housing market	hedonic pricing analysis of all single-family home sales in California over the time period 2007 to 2012	Incremental value for certified homes of 2.1% for the most conservative estimate (5% and +$8400 on average). The premium offset in theory the input cost for those buildings ($4000-$10 000) There evidence of spatial variation in this capitalization such that both environmental ideology and local climatic conditions play a role in explaining the variation in the green premium across geographies.
Bruegge et al. (2016)	EnergyStar program in Florida between 1997 and 2009	Hedonic price model on panel data using pooled OLS	There is a price premium for EnergyStar homes but that premium fades rapidly and disappears over time as building codes improve the non-labelled new buildings.
Ben. J Kaufman, (2010)	study for the Washington state residential Market	Times series analysis	Seattle market value +9.1% on average and factor 4 in vacancy rate. There are periods when non certified houses priced higher than certified ones: signs of market stress.
Europe			
Brounen & Kok (2009)	18 000 certified houses in the Netherlands	Hedonic sales price model	Market value : +2,8% and sells quicker Energy label has more impact than multilevel certification Authors find that energy performance sells better when housing market is not under stress. They also underline the lack of "energy literacy"
Brounen and Kok (2011)	32000 certified houses in the Netherlands	Hedonic sales price model	Premiums for ABC labels (10%,5.5% and 2%) and discounts for E, F and G labels (0.5%, 2.5%, 5%) with respect to D labels.
Alberini et al (2014)	Car sales in Switzerland between 2000 and 2011	Hedonic price model on panel data using regression discontinuity design	The effect of A label on a car price is approximately 5%. A fuel economy premium is consistent with low discount rate (2.5%)

A. de Ayala et al. (2016	Energy efficiency rating in the national Spanish housing market (1507 obs)	Hedonic price model with ABC label and city dummy	ABC homes are priced 9.8% higher than D, E, F or G homes. ABCD labels have a 5.4% premium compared to EFG. But only 10% of Spanish homes have A,B or C energy efficiency rating.
European Commission, DG Energy (2013)	Austria, Belgium, France, Ireland and UK	Hedonic price controlling for regional and density factor using dummy variables	Positive premium in both market and rental values for several European cities except one (Oxford). The price gap ranges from 2% to 11% in market value and from 1% to 5% difference in renting value
Cajias and Piazolo (2013)	2630 building observations from 2008 to 2010 on the German residential sector	Hedonic price controlling for regional and building specific factors	Elasticity of energy conservation on market value of 0.45 and 0,08 for rental value
Hyland et al. (2013)	15 060 buildings on the Irish residential market	Logit estimation using Heckman procedure (less than 5% of obs. Had EE rating)	Price premiums for A, B, and C housing of 9.3%, 5.5% and 1.7%) and price discount for E, F and G of 0.4%, 10% and 6%)
Kholodilin et Michelsen (2014)	Berlin housing market (both residential and rental sector)	Hedonic regressions with comparison of implicit prices and the net present value of energy cost savings/rents	Energy efficiency is capitalized in house prices but there is a landlord-tenant dilemma". The implicit price of energy efficiency in a tenant-occupied dwelling is below the level of owner-occupied by a factor of 2.5
Fuerst et al. (2015)	333 095 dwellings sold at least twice between 1995 and 2012 on the English residential market	Hedonic price model	Price premiums for A/B or C (5%, 1.8%) and discounts for E and F (0.7% and 0.9%) but there is considerable variation across regions and property types
City of Darmstadt, Germany (2010)	City of Darmstadt, Germany	Continuous Energy consumption criteria	Market value increases +0,38€/m² for housing that consumes less than 175kWh/m²/year and + 0,50 € / m² for housing that consumes over 175 kWh/m²/year
Savi et al. (2011)	Market value for Swiss housing market with MINERGIE green certification between 2008 and 2010	Times series and qualitative survey	MINERGIE house costs +6.3% (15% in 2002) on average and reduces energy charges by 0.6% each year. N 2010 Houses market value +7% Collective dwellings : market value + 3.5 %, Rent value : + 6 %
Claudy and Michelsen (2016)	Estimate the influence of housing market features on the	Structural Equation Modelling	Regional housing market fundamentals (vacancy, income levels, and expectations) influence the energy performance of the

	regional energy consumption through housing quality		housing stock and the resulting energy consumption. Weak fundamentals lead to weak incentives to invest in housing quality.
France			
DINAMIC (2013, 2015)	Sales of 200 000 houses in 2010 at « good state » according to 8 climate and 5 price zones	Spatial Estimation Model (hedonic models using localization variables)	The study concludes that each energy label contains a 5% average price gap.
ADEME (2011)	Low Consumption (<50kwh/m²/year) Building labels for new and old dwellings	Qualitative and field experience approach on 20 deep retrofit homes followed over time.	Market value for renovated buildings increased from 5% to 22% (very dependent on energy heating source) In the construction market, green value is estimated at 5,5% in collective dwellings (13500€/flat) and 6% in individual houses (variates according to energy source)

SOURCES: AUTHOR'S REVIEW

8.2. Robustness Checks

TABLE 13. BOOTSTRAP ESTIMATION OF TOBIT REGRESSION ON INDIVIDUAL HOUSES DATA SAMPLE

	Individual Houses		
TOBIT regression for frontier's residuals in levels censored to [0;1] with bootstrap standard errors	DEA residuals	Bootstrapped interval (Normal Based 95%)	
Energy efficiency Grade ABC	-0.0107***	-0.0168	-0.004518
	(0.0031566)		
Number of Rooms	0.0207***	0.01814	0.02328
	(0.0013118)		
General State	-0.00444**	-0.00868	-0.0002
(ref=bad or unknown)	(0.002164)		
Pool	-0.0206***	-0.2034	-0.15982
	(0.006225)		
Constant	-0.182***	-0.20348	-0.1598
	(0.0111377)		
Sigma	0.0329***	0.030754	0.0349643
	(0.000698)		
Observations	1,185	1,185	1,185

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

SOURCE. AUTHOR

TABLE 14. BOOTSTRAP ESTIMATION OF TOBIT REGRESSION MODEL ON COLLECTIVE DWELLINGS DATA SAMPLE

	Collective Dwellings		
TOBIT regression for frontier's residuals in levels censored to [0;1] with bootstrapped standard errors	DEA residuals	Bootstrapped interval (Normal Based 95%)	
Energy efficiency Grade ABC	-0.0122***	-0,018995	-0,005466
	(0.00345)		
Number of Rooms	0.0241***	0.02195	0.0263278
	(0.001117)		
Extra Bathroom	-0.0444***	-0.0586416	-0.0301792
	(0.00726)		
Construction period	-0.00612**	-0.111242	-0.0011158
(ref= before1975)	(0.00255)		
Parking	-0.0132***	-0.01784	-0.00855
	(0.00237)		
Outdoor	-0.0150***	-0.019982	-0.010048
	(0.00253)		
Constant	0.0373***	0.01551	0.05915
	(0.011132)		
Sigma	0.0420***		
	(0.000752)		
Observations	1,588		

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

SOURCE. AUTHOR

8.3. Green property discount

TABLE 15. STAGE 2 REGRESSION ON FRONTIER RESIDUALS FOR COLLECTIVE DWELLLINGS

Collective Dwellings	DEA	MLE
EPC ABC	ref.	ref.
DE (grouped)	0.0121***	0.0112
	(0.00329)	(0.00765)
FG (grouped)	0.0128***	0.0273***
	(0.00400)	(0.00930)
nbr_pieces_quant	0.0242***	0.0157***
	(0.000992)	(0.00231)
SDB_dum	-0.0445***	-0.0616***
	(0.00600)	(0.0140)
Constr_dum	-0.00614**	-0.0370***
	(0.00289)	(0.00674)
Parking_dum	-0.0131***	-0.0103*
	(0.00248)	(0.00550)
terrasse_balcon_jardin	-0.0149***	-0.0390***
	(0.00249)	(0.00578)
Constant	0.0246**	-0.0398***
	(0.0104)	(0.00579)
		0.0831***
		(0.0242)
Sigma	0.0420***	0.0976***
	(0.000752)	(0.00173)
Observations	1,588	1,588

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

SOURCE: AUTHOR.FROM BIEN DATASET

TABLE 16. STAGE 2 REGRESSION ON FRONTIER RESIDULAS FOR INDIVIDUAL HOUSES

Individual Houses	DEA	MLE
ABC	Ref.	Ref.
D	0.0102***	0.0193**
	(0.00320)	(0.00952)
E	0.0108***	0.0386***
	(0.00328)	(0.00989)
F	0.0111***	0.0624***
	(0.00372)	(0.0112)
G	0.0132***	0.119***
	(0.00431)	(0.0128)
Nb of Rooms	0.0209***	0.00675***
	(0.000689)	(0.00193)
General state	-0.00411*	
	(0.00218)	
Pool	-0.0204***	-0.0412***
	(0.00459)	(0.0137)
Construction Period		-0.0412***
		(0.00699)
Parking		-0.0198***
		(0.00671)
Constant	-0.194***	
	(0.0101)	
Observations	1,185	1,185

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

SOURCE: AUTHOR.FROM BIEN DATASET

8.4. Energy retrofit cost analysis

TABLE 17. ADEME UPFRONT COSTS PER HOUSING TYPE, CONSTRUCTION PERIOD AND HEATING TYPE

Housing Type	Initial Energy Consumption (kWep/m²/year)	Energy Label (before=> after)	Energy Consumption after retrofits (kWep/m²/year)	Energy Gain (kWep/m²/year)	Surface	Global Investment Cost	Investment /m²
LC 1960 Gas	275	E=>B	82	193	50	12 258 €	245 €
LC 1970 Heat	205	D=>B	73	132	50	32 223 €	644 €
LC 1975 Gas	344	F=>B	86	258	68	28 816 €	424 €
LC 1985 Elec	240	E=>B	83	157	70	33 508 €	479 €
MI 1981 Elec	490	G=>B	86	404	104	48 348 €	465 €
LC 1970 Fuel	285	E=>B	75	210	106	20 747 €	196 €
MI 1975 Gas	317	F=>B	86	231	128	55 716 €	435 €
MI 1955 Fuel	400	F=>C	115	285	136	37 000 €	272 €

SOURCE: ADEME DATA FROM CASES STUDY, CALCULATION FROM AUTHOR

NOTES: CASES ARE OBTAINED FROM ADEME IN 2010 FOR INDIVIDUAL HOUSES (MI) AND COLLECTIVE DWELLINGS (LC) ACCORDING TO THE MAIN HEATING TYPE (ELECTRIC, GAS, FUEL AND CENTRAL HEATING)

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