Edouard Civel [a,b,d,*], Nathaly Cruz [a,b,c]

[a] *EconomiX, Paris-Nanterre University, France*
[b] *Climate Economics Chair, France*
[c] *Centre Scientifique et Technique du Bâtiment, France*
[d] *Saint-Gobain Recherche, France*

[*] *Corresponding author:* edouard.civel@chaireeconomieduclimat.org

Green, yellow or red lemons?

Artefactual field experiment on houses energy labels perception.

(Working Paper)

Abstract

Labels are increasingly popular among policy-makers, companies and NGOs to improve consumers awareness, especially about environmental footprints. Yet, the efficiency of these informational tools is mostly assessed as their ability to shift behaviors, whereas their primary goal is to enable people to discriminate labelled goods. This paper studies how the complex information displayed by Energy Performance Certificates, energy labels introduced by the European Union for housing, is processed by real economic agents. Through a randomized artefactual field experiment on 3,000 French subjects, we test the impact of these labels on people's perception of a home energy performance.

Results evidence that 24% of subjects did not pay attention to the energy label. We isolate a few socio-demographic characteristics which are decisive in this changing attention, namely gender and the owner-occupant/tenant status.

Among attentive subjects, beta regressions show that energy labels' efficiency to transmit information is mixed. Subjects do identify separately each label's grade, but their judgment is based on the deceptive visual design of the label and blurred by idiosyncratic features. Aggregated reading is then interpreted as Bayesian: subjects use the label information to revise their beliefs on energy quality.

Keywords: Information treatment ; Experimental economics ; Cognitive psychology ; Green Value ; Energy efficiency.

JEL classification: D03 ; D12 ; D83 ; L15.

1 Introduction

In his seminal article "The market for lemons", Akerlof (1970) brought out how products of uncertain quality could be unfairly valued by economic agents. Half a century later, labels and certificates have spread to tackle these informational failures: information imperfection and asymmetry plague eco-friendly consumption as underlined by Cason and Gangadharan (2002) and Kulsum (2012), and deepen the energy-efficiency gap identified by Jaffe and Stavins (1994). In that respect, the European Union has introduced a mandatory certification of energy-consuming goods: the Energy Performance Certificate. This is key in the real estate sector, as buildings account for 39% of Europe final energy consumption, and even slightly more in France, Germany, Italy and in the United-Kingdom, where they respectively reach 42%, 41%, 41% and 40% of those countries final energy consumption (European Commission (2017)).

Following the European directive 2002/91/EC of the European Parliament and of the Council of 16 December 2002, Member States had to implement energy performance certificates (designated as EPC or energy label in the present article), which should be made available when buildings are constructed, sold or rented out. This directive was transposed in Member States legislations, and came into force by 2008 for most countries. This regulation aims at enabling any investor, household or company, to evaluate a building's energy quality. In the long-run, this policy is expected to favor green buildings by a differentiation in real estate prices according to energy-efficiency. However, this instrument effectiveness is challenged in several countries, both by industrials (like the Royal Institution of Chartered Surveyors in the United Kingdom) and by households (like UFC, the national association of consumers in France). Firstly its effect on prices is questioned. Secondly, EPC itself is contentious. If it reduces information asymmetry between the buyer and the seller, it suffers from several weaknesses. On the one hand, EPC is poorly reliable, as this indicator is not measured but estimated. Diagnosis is either drawn from a theoretic calculus, which output is publicly known to be volatile, or from the tenant energy bills, which are heavily reliant on agents heating behavior. On the other hand, EPC design itself is criticized. Using colors, letters and arrows of different sizes, it aims at inducing a heuristic judgment, but its intrinsic information is a complex expert knowledge - the estimated average primary energy consumption in kWh per meter-squared and per year. Technical seriousness and psychological salience of this label then undergo severe attacks, but until now there is no academic study aiming at understanding how houses energy labels are actually perceived by households.

The purpose of this article is precisely to evaluate if Energy Performance Certificate is an efficient tool to enable households to differentiate houses according to their energy quality. This is a prerequisite for the emergence of a green value, *i.e.* for capitalization of energy performance. In the second section we review the academic research interested in labels efficiency: while a growing number of studies focus on labels' efficiency to induce a shift in agents' behavior, this review underlines a lack in the understanding of the cognitive processes at work when households face an energy label. This second section enables us to formulate three conjectures through which we analyze the efficiency of Energy Performance Certificates. The third section describes our experimental design and our econometric strategy: we displayed a real estate advert with a randomized energy performance certificate to a representative sample of the French population, and we mined their perception of the house's energy quality. Results are presented in the fourth section: subjects exhibit uneven attention to the label, depending on gender and owner-occupant/tenant status. We find out that Energy Performance Certificates are effective, subjects relying substantially on the grade indicated to modify their beliefs on energy quality. However this perception of energy quality remains asymmetric regarding label's grades, which prevents a clear-cut differentiation of the greenest buildings. Moreover, we evidence that age and experience with the real estate market engender skepticism towards EPCs, underlying some of the weaknesses of this public policy instrument. Section five deepens our analysis on the reading of the EPC: we show that subjects follow the visual design of the label to judge the energy quality of the house, whereas this design is deceptive in the favor of inefficient dwellings. Nonetheless, subjects do not perceive EPC as perfectly informative, their reading is more based on a bayesian approach. Section six concludes with our main findings.

2 Literature review: labels efficiency

In this section, we review the recent literature in behavioral economics underlining the necessity of having a cognitive approach of information when dealing with labels. If this approach is widely spread in the literature on food labels, we show that the literature on houses energy labels still lacks a cognitive analysis in the treatment of energy efficiency information by households.

2.1 Why do we need a psycho-economic analysis of labels?

In order to achieve efficient environmental policies, where multiple goals intertwine, several economic instruments are used nowadays by governments, following the well-known rule stated by Tinbergen (1952). Those instruments are split into three broad categories by Stavins (2003): charge systems, tradable permit systems, and policies reducing market frictions. The last category includes programs that aim at enhancing information. Labels belong to this category. A large strand of literature has since studied which of those instruments should be used and how they should be combined in order to achieve significant improvements in eco-production and eco-consumption: on the specific issue of energy efficiency, see contributions of Olsen (1983), Sardianou (2007), Kern et al. (2017), Collado and Díaz (2017). The contribution of Santos et al. (2006) is especially interesting as it proposes a strategy relying both on theory and on stakeholders participation to design different instruments: their paper evidences that ecolabelling has a great potential among environmental policy instruments, giving back power to consumers in the choice of sustainable products and favoring a healthy competition between firms to increase environmental quality of their services.

However, as labels use spreads, both recent theoretical and empirical economic research underline their behavioral limits. Papers modeling the presence of multiple eco-labels, like the ones of Ben Youssef and Abderrazak (2009), Brécard (2014), Baksi et al. (2017) and Brécard (2017), forebode limits in consumers' ability to discriminate different labels' information. They underline the need for a psychological approach when dealing with labels. This conclusion is also favored by empirical evidence: in their vast econometric analysis of wholesale used-car transactions, Lacetera et al. (2012) demonstrate the heuristic thinking of consumers: even when buying a high-value durable-good, people use heuristics when processing information, and these cognitive shortcuts can lead to large amounts of mispricing.

In "Maps of Bounded Rationality: Psychology for Behavioral Economics", Kahneman (2003) explains that there is not one but three cognitive systems which can be involved with information treatment: perception, intuition and reasoning. While perception and intuition share a lot of characteristics in the process of information, reasoning refers to a significant mental effort. This distinction is important when designing labels: is the information displayed going to get a lot of attention from consumers, or will they use heuristics to process this information quickly? It will depend on the amount of other information they have to process and on the time they have in order to make a decision. A good illustration of this duality between fast and slow thinking can be found in the article by Miller et al. (2016). They conducted a field experiment in a Florida school on the selection of healthy diet by students. They demonstrate that both an incentive to use the reasoning system, by pre-ordering lunches, and an incentive to guide intuition, a nudge when pre-ordering, can significantly improve a healthy diet choice among treated students compared to the control group.

In this context, the role of label is twofold: providing information to consumers and inducing specific intuitions. The design of labels has then to be relevant to both convey information and set up good heuristics. Therefore, the cognitive salience of labels is paramount to their efficiency. A badly designed label could have counterproductive effects, as shown by LaVoie et al. (2017) in their psychological analysis of graphic cigarette warning labels. These authors find out that these labels could have negative effects on the reduction of tobacco smoking, due to the psychological shortcuts of perception and intuition. Dealing with eco-labels, Teisl et al. (2008) points out the importance of "well-designed labeling practices as they significantly impact individuals' perceptions".

2.2 Labels: the case of food

Economic literature on food labels has grown much faster than the one dealing with its twin issue, energy labels. Two main lessons drawn from food labels studies are useful for our research. First, studies on eco-labelling food evidence that the impact of labels is strongly reliant on consumer's type. The work published by Panzone et al. (2016) shows that socio-demographic characteristics have a great importance in people's choices of sustainable consumption. Moreover, Brécard et al. (2009) and Steiner et al. (2017) underline that these characteristics have a significant impact in people's relation to labels. Last, the importance of prior beliefs is highlighted by Shewmake et al. (2015). But this part of eco-labels' literature is not yet interested in cognitive salience of food labels, and this issue is raised by academics concerned with nutritional labels. Those are trapped in a thorny issue to sort out which would be the best front-of-pack labelling strategy: Guideline Daily Amount or Traffic Light? Hodgkins et al. (2012), Crosetto et al. (2016), Muller and Prevost (2016) and Enax et al. (2016) use field or lab experiments to understand how salient nutrition labels may help consumers to choose healthy diets.

The literature on food labels explicitly highlights the importance of people's characteristics and cognitive salience to have an efficient label. However these conclusions should not be directly duplicated into our research object. Indeed food labels aim at influencing people while they are buying multiple low-value and non-durable goods, whereas energy labels target purchases of high-value and durable goods, especially in the case of real estate.

2.3 Labels: the case of energy

As shown in the articles of Schley and DeKay (2015) and Santarius and Soland (2018), when dealing with energy efficiency it is necessary to consider the cognitive shorcuts used by consumers as they have a decisive impact on their energy conservation behaviors. Energy labels have mostly focused on the specific case if home appliances: refrigerators, light bulbs, washers, tumble dryers... The early study of Verplanken and Weenig (1993) on refrigerators choices started to get interested in the cognitive response of consumers to graphical energy labels. However the main psychological limit studied is time pressure. Min et al. (2014) demonstrated the impact of labeling light bulbs energy costs on implicit discount rates in a field experiment, giving also clues on the psychological consequences of labels. A field study conducted by Stadelmann and Schubert (2018) tests the effect of different label designs on purchases of appliances by households, and Andor et al. (2016) investigated in a discrete-choice experiment the role of EU energy labels for refrigerators in the heuristic thinking of consumers. The recent empirical analysis from Houde (2018) evidences that according to the consumer you are looking at, labels efficiency in shifting behaviors varies.

But all these studies consider the efficiency of EPCs as their ability to change consumers' behaviors, whereas the primary function of energy labels is to enable consumers to differentiate goods according to their energy performance. A very limited number of research papers study the influence of energy labels on consumer assessments of products, whereas it is the primary role of these labels. Waechter et al. (2016) conduct a very interesting study on different designs of energy labels for home appliances (refrigerators and coffee machines), suggesting to modify the current design of EU energy labels for these products. However this sparse literature on cognitive salience of energy labels is only dealing with home appliances. As far as we know, there is not until now any cognitive analysis of houses energy labels. Recently, there has been numerous studies dealing with the green value of buildings that is supposed to derive from energy labels: see Fuerst and McAllister (2011) for office buildings in the United States, Brounen and Kok (2011) for dwellings in the Netherlands, Hyland et al. (2013) for homes in Ireland, Kahn and Kok (2014) for houses in California, or Fuerst et al. (2015) for residential buildings in England. Meta-analysis computed by Ramos et al. (2015) highlights the contrasted results of this literature. A recent article from Olaussen et al. (2017) wonders if energy labels really do have an impact. A potential limit on these analyzes could be their assumption that energy labels are perceived as perfect information by households.

Our research innovates from the literature described above on two aspects. First, we study perception of houses energy labels, while previous studies on energy labels perception exclusively focused on appliances, which characteristics are much less diverse than those of houses. Second, we assess efficiency of energy labels on their fundamental function, enabling households to differentiate homes according to their energy performance, and not on the second or third generation of consequences expected as they are usually assessed.

2.4 Conjectures

Consistent with the literature, we formulate several conjectures on the role of EPC in the perception of a house energy quality. As highlighted by academic papers published on food labels, socio-demographic characteristics could play a key role in the importance subjects attribute to energy labels. Indeed, the importance given to the intrinsic information displayed by the EPC could vary among individuals, and the design of EPC could be unequally salient to them. We investigate this research question by testing the attention subjects pay to the EPC, as stated in conjecture 1.

Conjecture 1. *Attention to the Energy Performance Certificate is heterogeneous among subjects.*

Besides, EPC is not a new policy instrument, since it was enforced by law in France in 2007. We underlined in the introduction that its reputation among French citizens is heavily challenged by consumers associations. However, as academic literature exhibits that energy labels have an impact on houses market value, and then makes the hypothesis that EPC information is used by households, we want to test the conjecture 2.

Conjecture 2. *The Energy Performance Certificate affects subjects' perception of energy efficiency.*

The literature which investigates buildings' "green value" systematically represents the EPC as a categorical variable in their hedonic prices models, *i.e.* each grade of the EPC is a separate level of the energy quality. This modeling choice relies on two assumptions: firstly that reading of Energy Performance Certificate is based on their visual design and not on the intrinsic information conveyed; secondly assumption is that EPC is interpreted as perfectly informative on energy quality by households. We formulate these assumptions in the conjectures 3 and 4.

Conjecture 3. *Energy Performance Certificate reading is based on its visual design.*

Conjecture 4. *Energy Performance Certificate is treated as perfectly informative.*

3 Experiment, data and empirical methods

3.1 Experimental design

In order to measure EPC impact on perception of houses' energy quality, our experiment was administrated through an online survey on a sample of 3,000 individuals, representative of the French population. Experiment was tuned with pre-tests, firstly with thorough face-to-face interviews with a limited number of subjects, then with a first experiment online with 300 participants. If we refer to the classification made by Harrison and List (2004), our experiment can be described as an artefactual field experiment: the task and information given to participants are standardized like in a conventional lab experiment, but the subject pool is a representative sample of the French population.

The protocol was chosen to fit French housing market context: in France, energy performance certificates have to be displayed on real estate adverts since 2007, both for renting or selling, and is given to the new dweller at the signature of the purchase/rental agreement. However, as signature occurs after making real estate bid, the key moment when EPC can alter consumer's decision is when he takes a look at the real estate advert.

The experiment started with a welcoming message announcing that people were participating to a survey on the real estate market. This preliminary message did not mention that survey's topic was energy labels. Experiment was then split into 5 steps. In the first step, one out of eight real estate adverts was presented randomly to the subject. All adverts presented the same house, and only differed by the energy performance certificate. The real estate advert was built as a typical french house ad[1]. Among the eight adverts, one control advert did not display any energy label. The seven others were treatment ads, displaying the official energy performance certificate; each treatment indicated one of the seven categories of energy labels, from A to G. Instruction given to the subject was: *"Thanks for devoting a little time to carefully observe this real estate ad. Then please click on next to start the questionnaire"*. Participants were not time constrained, but once the questionnaire started they could not go back and see again the real estate ad or change previous answers. An example of these real estate ads can be found in appendix A.1. Each subject only faced one treatment; mean survey filling time was 12 minutes.

The experiment's second step consisted in questions about the different pieces of information displayed on the real estate ad, to observe which characteristics were more minded by participants. In the third step, participants had first to evaluate the energy performance of the house by a rating on a scale ranging from 0 (Very poor energy performance) to 100 (Excellent energy performance). This is the main dependent variable studied in following sections, to understand energy labels reading. In the fourth step, participants were asked which was the energy performance expressed by the energy label: it was a free expression space, which results will be used in the section 4.2 to investigate the determinants of subjects' attention to energy label.

The fifth step of the experiment consisted in several questions to evaluate subjects experience of real estate market and their understanding of houses energy performance. Socio-demographic characteristics of respondents were also collected in that section.

3.2 Data analysis

The 3,000 participants were on average 47.7 years old, and 47.6% of them were men. 66% of respondents declared owning their housing. These figures are in line with the French population over 18 years old: 49.4 years old and 47.7% of men, Insee (2018), two-thirds of owner-occupied dwellings according to Eurostat (2015). As the eight adverts (treatments and control) were randomly allocated among participants, each advert was globally presented between 363 to 396 times.

Data analysis is split in four parts. First one describes data through box-plots and density distributions of energy ratings for each treatment.

In a second part, we investigate the determinants of being attentive to the EPC, in response to the conjecture 1. Kolmogorov-Smirnov tests are applied to subjects who declared in the experiment not remembering anything about the energy label displayed on the ad they watched. Then a probit econometric model is built by using an ascendant stepwise method of optimization based on the Akaike Information Criterion. This probit investigates factors driving the attention to the energy label.

[1]Real estate ads displayed a title specifying price, living area, number of floors and approximative location, followed by several pictures of the house and, finally, a short paragraph describing house's characteristics as the description of the neighborhood, the number of bedrooms and bathrooms, the presence of a parking box, the heating system, and the window frames and glazing.

In a third part, we analyze EPC perception to test the conjecture 2. The Kolmogorov-Smirnov test is applied to pairs of ratings distributions to assess if perception of various grades is significantly different. In order to control for socio-demographic variables and to understand EPC impact, we investigate econometrically ratings given by subjects who received a treatment and declared remembering something about the energy label, *i.e.* attentive subjects. As this group is a subset of treated subjects, we control in our econometric analysis for a selectivity effect using the two-steps Heckman correction. In order to take into account the fact that ratings were constrained in the interval [0,100], and the intrinsic heteroskedasticity that derives from this condition, we built an econometric model based on beta distributions. This strategy enables a double analysis both on mean and dispersion of ratings' distributions. We implement the beta regression by an ascendant stepwise analysis.

In a fourth part, we firstly explore the stochastic dominance of subjects ratings to arbitrate if subjects reading of EPC is based on the grade or on the numerical information (primary energy indicated by the energy label). Secondly, we propose a bayesian model which replicates more realistically subjects responses.

4 Results

4.1 Data overview

4.1.1 Descriptive data

On Figure 1, we represent energy ratings' box-plots for the control group and the seven treatments. We observe that, as labels get "greener" (resp. "redder"), ratings shift towards good levels (resp. bad levels). In both ways, box-plots' width increases when labels become more extreme. Moreover, the median of the control group ratings is close to the scale center, just like the median of D-label treatment group ratings. This suggests that our real estate ad did not in itself strongly bias judgments on house energy quality. Between treatments, medians are correctly ordered: G is rated better than F, which is rated better than E, etc. Nevertheless we can note a small inversion between the medians of A-label and B-label groups. It seems also that G-label ratings are much more concentrated on the inferior boundary of our scale than A-label ratings are on the superior boundary.

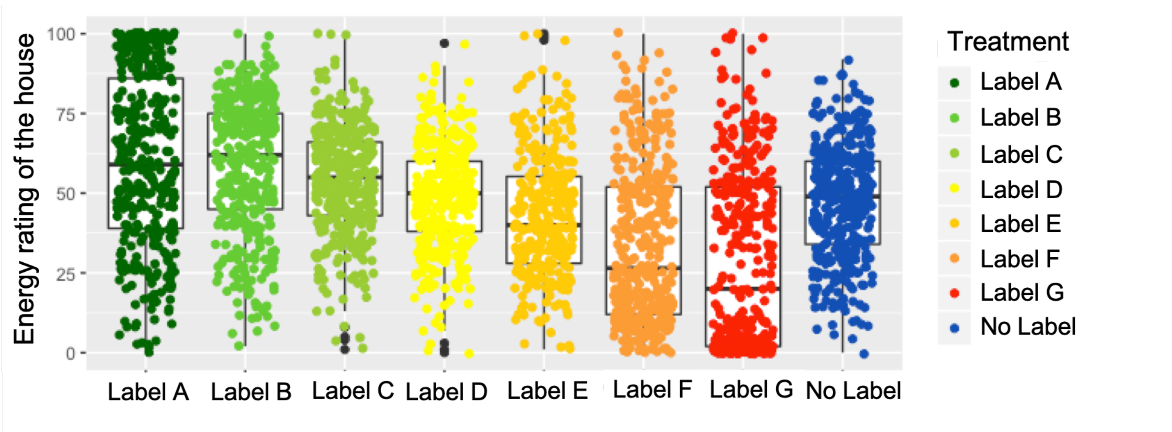


Figure 1: Box-plots of energy ratings

On Figure 2 we draw the empirical densities of energy ratings. Three main features can be drawn from these distributions. First, we can observe that distributions' modes are correctly ordered: they increase when shifting from label G to label A, and the mode of the central label D distribution is similar to the one of the control group (no label). Secondly, distributions are not "clear-cut": on the whole, people's perception of energy labels is not exact, distributions overlap each other. Thirdly, distributions which are not central exhibit a second mode, in the center of the rating scale. Thanks to the fourth step of our experiment, we were able to differentiate people who noticed the energy labels when watching the real estate advert to those who did not. We count overall 614 subjects who declared not remembering anything about the information displayed by energy label, instead one was present on the advert. There were similar numbers of inattentive subjects in the different treatments groups, with respectively 87 subjects for label A, 98 for label B, 92 for label C, 89 for label D, 75 for label E, 83 for label F and 90 for label G. When withdrawing from the samples those subjects, the second mode of distributions (located in the center of the scale) softens strongly in each distribution (see Appendix A.2). This result is consistent with the control group results: when people do not face an energy label or do not pay any attention to it, their energy ratings form a distribution centered in the middle of the scale. This corresponds to subjects' prior: this is the distribution of beliefs on energy quality before (or without) seeing the EPC but posterior to seeing the rest of the add.

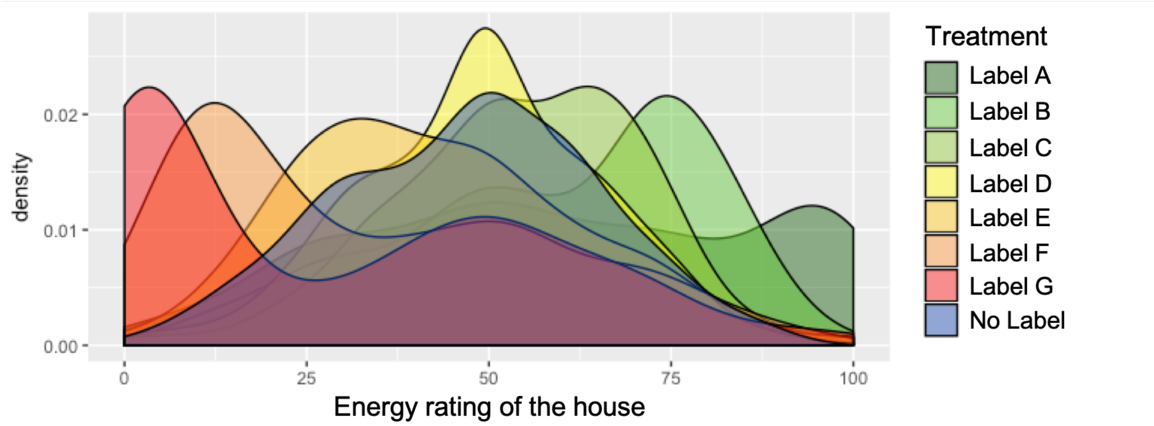


Figure 2: Distributions of energy ratings, all subjects

4.2 Determinants of attention to energy label

Another interesting result of our experiment is that 24% of subjects in the treatment groups did not take heed of the energy label displayed on the real estate advert. This information is available thanks to the analysis of subjects' answers to the question *"Which was the energy performance expressed by the energy label?"*. One quarter of treated subjects declared not remembering anything about the energy label which was displayed on their advert, even though remembering it was present. In order to test if energy labels had an unconscious impact on rating for these respondents, we replicate on the subset of these subjects the analysis of the previous section (see appendix A.3 for the corresponding distributions). In Table 1, the Kolmogorov-Smirnov test shows that we cannot significantly differentiate ratings given by subjects submitted to different treatments but who reported they did not take heed of the energy label. These tests demonstrate that there is no significant unconscious influence of energy labels. When subjects declare they did not pay attention to the energy label, their energy ratings of the house are unbiased by the energy label, and are not significantly different from the ones of respondents in the control group.

Table 1: Labels induced no significant difference between ratings of inattentive subjects

	Kolmogorov-Smirnov test							
	D statistic							
	Label A	Label B	Label C	Label D	Label E	Label F	Label G	No Label
Label A	0	0.12545	0.068709	0.070445	0.084915	0.076165	0.054945	0.13198
Label B		0	0.11771	0.095571	0.091038	0.12382	0.11033	0.14819
Label C			0	0.057523	0.11977	0.071055	0.11178	0.13692
Label D				0	0.11743	0.055414	0.092423	0.12909
Label E					0	0.11405	0.094905	0.078321
Label F						0	0.07907	0.16583
Label G							0	0.11872
No Label								0

Note: *p<0.1; **p<0.05; ***p<0.01

A relevant point for public policies is to estimate if some socio-demographic characteristics of subjects have an impact on the probability of being attentive to the energy label. To answer that question, we built a probit model, with a stepwise procedure minimizing the Akaike Information Criterion; we control the goodness of fit with the McFadden statistics and we check the relevance of explanatory variables using the Wald test. Selected variables are significant with a level of confidence of 90% or higher. Coefficients of the model can be found in Table 2.

Table 2: Determinants of the attention to the energy label

	Binary dependent variable:
	Attention to the Energy Label
Gender: Woman	$\mathbf{-0.292}^{***}$
	(0.055)
Owner-occupant	$\mathbf{0.157}^{***}$
	(0.058)
Housing search after EPC introduction	$\mathbf{0.112}^{**}$
	(0.056)
Region:	
Auvergne-Rhone-Alpes	−0.155
	(0.120)
Bourgogne-Franche-Comte	−0.082
	(0.157)
Bretagne	−0.098
	(0.151)
Centre-Val-de-Loire	−0.238
	(0.157)
Grand-Est	0.071
	(0.132)
Hauts-de-France	−0.108
	(0.127)
Ile-de-France	$\mathbf{-0.212}^{*}$
	(0.110)
Normandie	0.014
	(0.155)
Nouvelle-Aquitaine	−0.039
	(0.128)
Pays-de-la-Loire	−0.076
	(0.146)
Provence-Alpes-Cote-d'Azur	−0.112
	(0.130)
Constant	$\mathbf{0.781}^{***}$
	(0.110)
Observations	2,609
Log Likelihood	−1,430.782
Akaike Inf. Crit.	2,891.564
Note:	*p<0.1; **p<0.05; ***p<0.01

Four socio-demographic characteristics have a significant impact on the attention given to the energy label: gender, owner-occupant/tenant status, the fact of having been involved or not in a housing search since the introduction of EPC, and the region where lives the subject. Factors which appear not being significant deserve some comments: age, socio-professional category, revenue and education level do not exhibit a significant impact on the attention to energy labels (in Appendix A.4 we list all tested variables).

Among the four characteristics having a significant impact on attention, a first small effect, significant at 5% type I error, is linked to subjects' experience. When subjects have not been facing the real estate market recently, they are less attentive to the energy labels, a result which was expected as houses energy labels have been introduced a decade ago in France. Secondly, only one region exhibits a significant effect at a level of 10% on the attention to the energy label: it's *"Ile-de-France"*, the region of Paris. We interpret it as a market effect: this region's real estate market is under pressure, with prices two to three times higher than other regions. As energy prices do not depend if housing market is tense or not, the relative importance of energy costs in Ile-de-France is lower: a lower attention to EPC in that region is then understandable, as subjects from that area could be "desensitized" to this stake. This is consistent with the paper by Fuerst et al. (2015) investigating the green value in England: authors find no significant impact of energy labels on houses market price in London's area, while identifying one in the rest of England.

The effect of the owner-occupant status, in comparison to the tenant status, is interesting and significant at a level of 1% type I error. Subjects being owner-occupants were more attentive to the energy label. While tenants cannot take actions to improve the energy efficiency of their home, in France they have to pay for the energy bills. These split incentives in residential energy consumption are well described by Gillingham et al. (2012): authors show that tenants paying energy bills tend to consume less energy compared to tenants whose energy bills are paid by landlords. Whereas EPC effect on households expenses is as important for the tenants as for the owner-occupants, unexpectedly we evidence that tenants pay less attention to it. This weakens the hypothesis of a "use value" vision for energy efficiency: the EPC is not interpreted as an indicator of future savings on the energy bill. We suggest then that French households conceive information on energy efficiency as more relevant for the "patrimonial value" of their home rather than its "use value".

The most significant variable is not one of those previously mentioned: gender. This characteristic is significant with a 99.9% confidence level. When running the regression with control variables (revenue, age, education level, socio-professional category, age, size of the household), gender variable role does not weaken. In our sample, whereas women represented 52% of subjects facing a real estate ad with an energy label, they represent 62% of inattentive subjects. Gender differences have been well documented in the academic literature, for instance in terms of attitude towards ethics, risk, competition and environmental quality. But gender differences in the attention to energy labels have not yet been reported in the literature as far as we know, and interpretation is not obvious. Roots of differences in genders' psychology have been widely explored by psychologists, sociologists and by clinicians, all of them acknowledging the role of both biological factors and socio-cultural ones. In order to investigate this difference in the information selection, we resort to the selectivity hypothesis, a theory developed and supported by various scholars working on consumers psychology and especially on advertising responses. This model owes a lot to the seminal work of Meyers-Levy (1986), who has also published recently a review on related works in the past twenty years, see Meyers-Levy and Loken (2015). The selectivity model posits that genders process information differently: females tend to be more comprehensive information processors, while males are more selective processors who tend to rely on heuristics and informations highly salient. Various empirical studies have strengthened this theory: many experiments are described in the papers of Meyers-Levy and Maheswaran (1991), Meyers-Levy (1994), Darley and Smith (1995), Miquel et al. (2017), and the meta-analysis of Putrevu (2001) and Wolin (2003).

In our case, this stream of research is highly relevant. Gender differences in information processing arise under two conditions: first when the volume of information is important, and second when information has different levels of accessibility and saliency. This is consistent with real estate adverts: on the one hand they exhibit informations highly available to the public, such as price, living area and location which are displayed in the title, pictures of the house or flat, and the energy efficiency label with colors. On the other hand they give precise information less easily available, as multiple details about the dwelling specified in the written description.

We identify three features of energy labels design which could induce this gender difference in the attention to the label. First the saliency of the design: using colors, letters and arrows of various sizes, it makes information about energy-efficiency easy to process so that males will tend to select more that kind of information than females. Secondly, the information design rely on a comparative analysis (the dwelling is positioned on a scale of energy performance), which increases males involvement, whereas females have been found to be less inclined to comparative informations, as shown by Chang (2007). Thirdly, the nature of information conveyed by the energy labels may as well have a gender-differentiating role: indeed the energy labels displays an information about the typical consumption of the dwelling, expressed in kWh per meter-squared and per year. This kind of highly technical information has been shown to appeal more male subjects than female ones, for instance see Putrevu et al. (2004); furthermore, this technical information is poorly handy in itself, as its translation in terms of energy bills or thermal comfort is almost impossible, which makes it less attractive to female subjects.

The specific design of energy labels is then favorable to male subjects, which will tend to select more this information when evaluating the dwelling.

Several socio-demographic characteristics have a significant impact on subjects' attention to energy labels. Channels of this varying attention are attributed to diverse features, design of the EPC on the one hand and economic situation of the subject on the other hand. These results lead us to reject the conjecture 1.

Result 1. *Conjecture 1 is not supported by our experiment: socio-demographic characteristics disturb attention to the Energy Performance Certificate.*

4.3 Evidences of EPC impact

Beyond the attention to this informational tool, we want to analyze how subjects' cognitive systems "digest" it once they have paid attention to this information. Using the non-parametric Kolmogorov-Smirnov test, we check in subsection 4.3.1 if each grade is statistically perceived differently. In order to understand energy labels reading by attentive subjects, we use an econometric strategy based on beta regressions. We aim at explaining how both EPC and socio-demographic characteristics affect energy quality perception and how they interact. Both the fact that energy efficiency ratings were confined in a finite interval and the skewness of labels' ratings distribution justify this approach. In subsection 4.3.2 we detail this strategy, while subsection 4.3.3 presents the results of our regressions.

4.3.1 Statistical evidence of EPC impact

As descriptive data underline that all distributions overlap, and that several distributions have almost the same means and close modes, a legitimate question arises: are these distributions significantly different? In order to answer it, we use the nonparametric Kolmogorov-Smirnov test on attentive subjects. Results shown in Table 3 exhibit that all energy ratings distributions drawn from the treatments are significantly different. However distribution derived from attentive subjects who received the treatment "label D" is not significantly different from that of the control group.

Table 3: Significance of the difference between ratings of attentive subjects

	Kolmogorov-Smirnov test
	D statistic
Label A vs Label B	0.2007***
Label B vs Label C	0.2391***
Label C vs Label D	0.1759***
Label D vs Label E	0.2088***
Label E vs Label F	0.3294***
Label F vs Label G	0.2899***
Label D vs No Label	0.0855
Note:	*p<0.1; **p<0.05; ***p<0.01

Those results demonstrate that each level of EPC induces a significantly different perception. Label A is perceived differently from label B, which is perceived differently from label C, etc. Nevertheless, label D did not induce a significantly different perception from the real estate advert without label, evidencing that central label D is used as a reference category. While some policy-makers advocate for reducing the number of classes of energy labels, arguing that seven classes are too many and that consumers gather good classes on the one hand and bad classes on the other hand, our results tend to demonstrate the opposite point. Even if distributions overlap, they are significantly different. As this test is univariate, we extend the analysis with beta regressions.

4.3.2 Beta regression model

Beta regressions are used to identify the main factors driving the behavior of a variable following a beta distribution. The beta distribution is a family of continuous probability distributions defined on the interval [0,1] parametrized by two positive shape parameters, usually denoted by α and β. Moments such as the mean and the variance of a beta distribution depend on both of these shape parameters and are then linked. Beta regressions proposed by Ferrari and Cribari-Neto (2004) use this principle of two separated but linked moments: the first one represents the mean of the distribution μ, while the second is a precision factor Φ. Those moments are parametrized as $\mu = \frac{\alpha}{\alpha+\beta}$ and $\Phi = \alpha + \beta$. For any variable y following a beta distribution, this parametrization enables a new writing of the classical moments of the distribution.

$$E[y] = \int_0^1 y f(y;\alpha,\beta)dy = \frac{\alpha}{\alpha+\beta} = \mu \tag{1}$$

$$Var[y] = E[(y - E[y])^2] = \frac{\alpha\beta}{(\alpha+\beta)(\alpha+\beta+1)} = \frac{\mu(1-\mu)}{1+\Phi} \tag{2}$$

A strength of these beta-regressions is that parameters μ and Φ can be explained by different sets of regressors. We use a regression that follows the same α and β values that describe the distribution, and obtain then two different sets of regressors associated to each parameter μ and Φ. In the selection of the first set of regressors, we focus on the mean, assuming the precision parameter constant. Once this first set of variables driving the mean identified, we look for variables affecting the precision parameter. That strategy enables to correct the heteroskedasticity issues intrinsic to the beta distributions. Estimators[2] maximize the log-likelihood function and explain moments of the distribution while not making the hypothesis of homoskedasticity.

We implement the beta regressions proposed by Cribari-Neto and Zeileis (2010) in an ascendant stepwise applied to our two groups of subjects, isolated thanks to the previous section. The first group gathers subjects whose real estate ad did not display an energy label, *i.e.* the control group. The second group gathers subjects who did face an energy label and were attentive this information : we call them "attentive subjects". The first group counts 391 subjects, the second group counts 1,968 subjects. Tables 4 and 5 present beta regression results when we authorize 10% level of type I errors in the selection of explanatory variables. Tested variables are the ones used in the previous section and presented in Table 7 (see Appendix A.4).

4.3.3 Econometrical evidence of EPC impact

We apply beta-regressions to two groups of subjects: the control group, who faced not any EPC, and attentive subjects in the treatments (who faced an EPC and paid attention to it). Table 4 presents regressors selected for their significance in the mean model for the control group. No significant variables were found for the precision model applied to the control group. Two variables exhibit significant impacts on subjects rating of the house energy performance: education level of the subject and the climate indicator of his county. Education level has an impact for one category: subjects with the highest level of education tend to underrate the energy performance of the house, while subjects with lower education levels (e.g. bachelor levels) or subjects with an education level below the baccalaureate do not rate differently the house energy quality. The climate indicator, depending on the county where the subject lives, corresponds to the annual need for heating due to the climate, expressed in degrees. The negative coefficient for this variable means that when subjects live in colder counties, they tend to underrate the energy quality of the house all other things being equal. However the explanatory power of this model is quite low: pseudo-R^2 is evaluated at 5.5%. These two effects are then not sufficient to explain the centered symmetric distribution of energy performance ratings made by subjects in the control group (see appendix A.3). This heterogeneity in ratings does not result exclusively from the systematical biases identified (education and climate) but also from idiosyncratic reading of the real estate ad: each subject perceives and treats differently the various pieces of information (as the pictures and information about heating system and windows).

A similar procedure is applied to subjects exposed to an energy label and attentive to it. However, there is a non-random selection for this group, as we have shown in Table 2 that some variables have a significant impact on the probability of paying attention to the energy label. We use the Heckman correction in two steps to control for this selection bias: the inverse Mills ratio is calculated from the probit model discussed in section 4.2 and used as a control variable. Results are reported in Table 5. The EPC displayed on the real estate ad and the age category of the subject are both significant at a 1% level, the dummy for having been looking for housing since the introduction of EPC is significant at a 5% level in the mean model. In the precision part of the model, only EPC is significant. The inverse Mills ratio does not exhibit significance at common levels, we then reject the hypothesis of a sample selectivity effect. Analysis of these regressions is threefold: EPC is highly informative and its reading is consistent with the design,

[2]See contributions by Espinheira et al. (2008) and Simas et al. (2010).

Table 4: Factors influencing the mean of energy ratings for subjects in the control group

	Dependent variable: House energy rating	
	Mean model	Precision model
Education level:		
Below baccalaureate (CAP, BEP)	0.169	
	(0.120)	
Baccalaureate	Reference	
Baccalaureate + 2 years (BTS, DUT)	−0.162	
	(0.117)	
Baccalaureate + 3 years (Licence)	−0.108	
	(0.135)	
Baccalaureate + 5 years and more (Master, PhD)	**−0.269****	
	(0.121)	
Climate indicator	**−0.00001****	
	(0.000)	
Constant	**0.441***	**5.8390*****
	(0.246)	(0.387)
Observations	391	
Pseudo-R^2	0.055	
Log Likelihood	106.758	
Note:	*p<0.1; **p<0.05; ***p<0.01	

but older generations, more exposed to this label, might be more skeptic. Moreover, label A perception stands out as noisier.

Table 5: Factors influencing mean and precision of energy ratings for attentive subjects

	Dependent variable: House energy rating	
	Mean model	Precision model
Energy Performance Certificate:		
Label A	**0.522*****	**−1.371*****
	(0.084)	(0.107)
Label B	**0.536*****	**−0.378*****
	(0.067)	(0.110)
Label C	**0.223*****	0.046
	(0.061)	(0.111)
Label D	Reference	Reference
Label E	**−0.393*****	**−0.330*****
	(0.069)	(0.114)
Label F	**−0.530*****	**−1.022*****
	(0.077)	(0.107)
Label G	**−0.719*****	**−1.212*****
	(0.086)	(0.111)
Age category:		
18-24 years old	Reference	
25-34 years old	−0.110	
	(0.077)	
35-49 years old	**−0.329*****	
	(0.072)	
50-64 years old	**−0.217*****	
	(0.075)	
Over 65 years old	**−0.198****	
	(0.078)	
Housing search after EPC introduction	**−0.108****	
	(0.047)	
Inverse Mills Ratio	−0.258	−0.251
	(0.237)	(0.327)
Constant	**−0.235***	**1.975*****
	(0.136)	(0.156)
Observations	1,968	
Pseudo-R^2	0.213	
Log Likelihood	468.302	
	Note: *p<0.1; **p<0.05; ***p<0.01	

Firstly, EPC is highly informative for attentive subjects: the EPC grade is the main driver of energy ratings. Moreover, variables which were influencing the mean of energy ratings of the control group (see table 4) are cleared out for attentive subjects. Indeed in table 5, education level and climate show no influence on subjects' perception of energy quality. Hereof we can consider houses energy labels as efficient: when they are processed, subject characteristics which influenced their perception are pushed aside. When giving a look at model's coefficients, results evidence a reading consistent with the design. As labels worsen, the mean of energy ratings decreases, while upgrading labels increases energy ratings. Together with results of section 4.3.1, we can validate the conjecture 2.

Result 2. *Conjecture 2 is supported by our experiment: Energy Performance Certificate is effective in changing subjects perception of energy quality.*

Secondly, the model reveals that age category and temporal proximity of a real estate research have an impact on labels reading. Age seems to evidence a generational effect in energy performance certificates reading. Subjects in the mid-life and superior age categories (35-49 years old, 50-64 years old, and over 65 years old) exhibit a lower perception of energy quality indicated by the EPC. They tend to rate lower the energy quality of the dwelling when an energy label is displayed. This effect stands out as particularly strong for subjects between 35 and 49 years old. A potential explanation of this effect roots in the conjunction between inception date of EPC and the age of buyers on the real estate market. These certificates were introduced in France in 2007; the 35-49 years old generation have faced them in their first acquisition of a house or an apartment, as mean age to become an owner-occupant in France is 38 years old. This negative effect might then be linked to a bad experience with those certificates: the French national consumer association has been criticizing the credibility of houses energy labels numerous times since their introduction, as stated in their fourth and more recent study on the subject "Energy Performance Certificates: Stop the lottery" by UFC (2017). Our result is consistent with this study: subjects which have been dealing with energy performance certificates are more skeptical about them. The negative effect of the variable "Housing search after EPC introduction" strengthens this explanation.

A third lesson from our econometric analysis comes from coefficients analysis. In Table 5, coefficients point out a peculiar treatment of the top-graded EPC, the A-label, obvious at all significance levels. Given the proximity of A-label and B-label estimated coefficients in the mean model, we test the significance of the difference between all labels coefficients by building instrumental variables. It appears that {A;B} is the only pair of labels which coefficients are not significantly different in the mean part of the beta regression, while remaining strongly significantly different in the precision part of the beta regression. If labels A and B are perceived differently by subjects, in terms of mean the label A is not perceived as better than the label B, while in terms of dispersion label A reading is much less precise than label B reading. This stronger dispersion of energy ratings for the A-labelled EPC could either be due to a noisier perception of this grade, and/or to a weaker confidence in this grade. A potential explanation of this phenomenon is the relative scarcity of A-labelled houses in the French real estate market, which may raise skepticism among subjects when they see this specific label in view of the house's pictures displayed on the ad.

5 Treatment of Energy Performance Certificate information

We demonstrated in the previous section that EPC has an impact on energy quality perception. However, while EPC's grades are built following an absolute thermodynamical value (typical primary energy consumption in $kWh/m^2/year$), visual design of these grades is deceptive as it suggests that all of them cover the same ranges of absolute values, whereas they do not. In this section we explore the hypothetical readings of EPC and compare them with experimental results to refine our understanding of the cognitive treatment of the energy label.

5.1 Hypothetical readings of EPC

If we follow the hypothesis made by the usual modeling of energy performance certificates in the economic literature on the green value, we can compute the counterfactual distributions of energy ratings which would derive from different readings of EPC.

In view of the information given by Energy Performance Certificates, two alternative pure readings can be considered, either based on the thermodynamic value or based on the grade. Intrinsic information of EPC is expressed in primary energy ($kWh/m^2/year$), and grades correspond to different intervals of primary energy. However, the visual design suggests that all grades represent same length intervals of primary energy whereas they do not: as labels get "redder", they cover larger intervals of primary energy. For instance, the B-labelled EPC gathers thermodynamic values ranging from 51 to 90 $kWh/m^2/year$, while the F-labelled EPC goes from 331 to 450 $kWh/m^2/year$.

Then, in each treatment of our experiment, energy ratings of subjects should concentrate around different values according to their reading (following the intrinsic information or the grade). In the case of an energy-based reading, as label gets redder, means of ratings would be more outspread and intervals would get wider. On the contrary, in the case of a design-based reading, there would be a constant gap between the means of ratings and the width of intervals would remain constant.

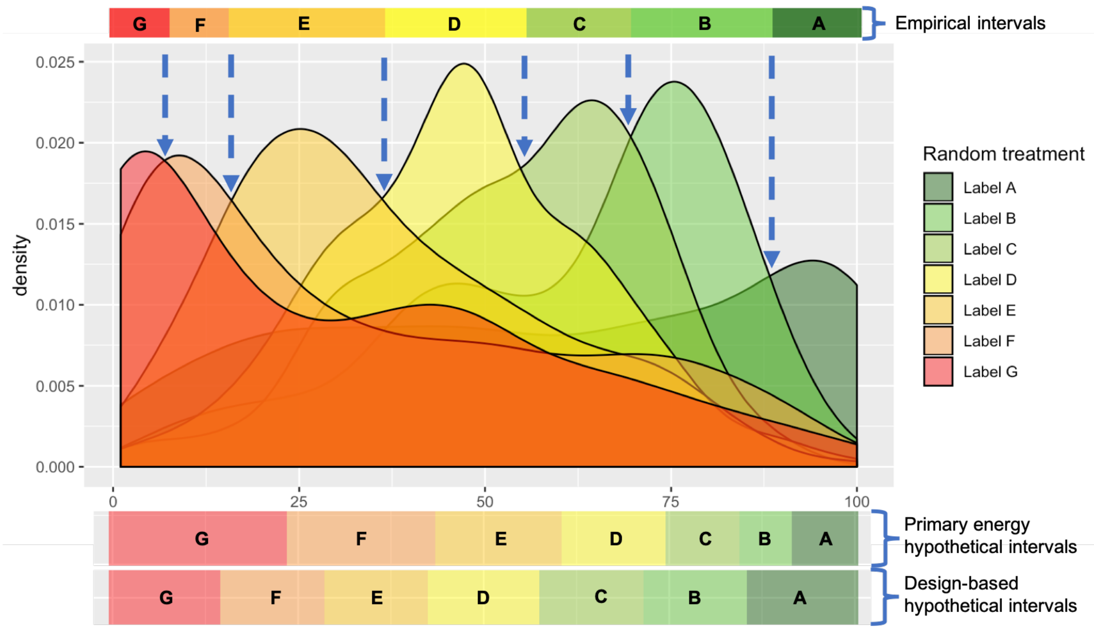


Figure 3: Hypothetical vs Empirical readings of EPC grades

On Figure 3 we represent those hypothetic intervals below the actual ratings made by subjects. In order to understand if subjects reading is based on the primary energy or on the visual design, we show upon the figure the empirical intervals. These empirical intervals are built using a stochastic dominance criteria which computes for each rating (from 0 to 100) which EPC grade has most probably been shown to the subject. For instance, the D-label is associated to the interval $[60; 74]$ in the primary energy reading, to the interval $[43; 57]$ in the design-based reading. Empirically the interval $[38; 53]$ is the one where ratings are more probably given by subjects who faced the D-label in our experiment.

Comparison between empirical intervals and hypothetical ones evidences that subjects reading is closer to a design-based one: indeed intervals for the same grade systematically overlap when considering empirical results and the design-based hypothesis. On the contrary, intervals deduced from the primary energy hypothesis are disjoint from empirical ones for a majority of grades (labels C, D, E and F). This result confirms the conjecture 3: reading of EPC is based on the label design and not on the intrinsic information on primary energy conveyed by it.

Result 3. *Conjecture 3 is supported by our experiment: Energy Performance Certificates reading is based on their visual design.*

Nevertheless, we observe that ratings distributions are not confined to their hypothetical intervals: on the opposite they overlap each other largely and dwell on the whole scale. This observation weakens the conjecture 4 which stated that EPCs were treated as perfectly informative. In Table 6, we compute the part of ratings made by attentive subjects belonging to the three kinds of previously built intervals: empirical intervals based on the stochastic dominance criteria, energy-based intervals built according to an hypothetical reading of EPC following its intrinsic information, and design-based intervals consistent with an hypothetical reading of EPC following its visual design.

Table 6: Dominance intervals cover a minority of actual ratings

	Proportion of attentive subjects ratings belonging to the interval		
	Empirical interval	Energy-based interval	Design-based interval
Label A	24%	24%	26%
Label B	47%	8%	40%
Label C	39%	9%	35%
Label D	44%	18%	36%
Label E	43%	19%	24%
Label F	30%	16%	18%
Label G	33%	48%	46%
Overall	37%	20%	32%

Overall, empirical intervals gather 37% of the ratings corresponding to their grade, while it is 32% for design-based intervals and only 20% for energy-based intervals. Empirical intervals systematically gather less than 50% of subjects ratings, no matter which treatment is considered. Together with the precision model of the beta-regression presented in Table 5 (which shows that when labels get more extreme, the ratings tend to be more disperse), this result evidences that EPC are not perfectly informative for subjects. We hypothesize that these distributions could be explained by a bayesian inference of EPC information.

5.2 Simulation of a Bayesian reading of EPC

Bayesian inference describes an updating process of prior beliefs thanks to an informative message. As messages are not perfectly informative, *i.e.* they are noisy, beliefs *a posteriori* will not necessarily be concentrated on the signal.

In our experiment, prior beliefs are described by the ratings distribution of the control group. Indeed those subjects face the same real estate advert as treated subjects, except that control group does not observe any EPC. Various information present on this ad enable subjects to form prior beliefs on the house energy quality, in both ways of a good or bad performance. For instance, the description of the house specify that heating system is based on a gas boiler and that windows have double glazing, clues that indicate generally an overall good energy performance. But at the same time, pictures suggest that the house was neither recently built or retrofitted, as the decoration for example is not a 'modern' one. The pictures then do not suggest a house benefitting from the state-of-the-art energy efficiency technologies. Those different information lead, together with subjects' personal experience, to the ratings distribution of the control group, *i.e.* the prior beliefs.

Treated subjects observe the same set of information from the real estate advert, plus an EPC grade. If, as we hypothesized, EPC is perceived as informative but imperfect by subjects, then ratings distribution of treated subjects should match with a Bayesian revision of prior beliefs. In order to test this hypothesis, we simulate a Bayesian inference of EPC information in subjects prior beliefs.

We start by estimating the parameters that describe best the 'beta distribution' of ratings in the control group. Overall, those ratings mean is 45.5, meaning that control group belief is slightly shifted towards bad quality. Shape parameters estimated to describe this empirical distribution are $\alpha = 2.466926$ and $\beta = 3.037094$. We compute the corresponding probability density function, the "prior" noted f^{prior}. Updated probability density function, posterior to the observation of label i, is written f_i^{post}. With x being a level of energy quality on the rating scale, $Pr_x(i)$ is the probability of having observed the label i when the energy rating given is x. We compute posterior beliefs (*i.e.* Bayesian revision of beliefs thanks to the observation of the label i) as follows:

$$f_i^{post}(x) = \frac{f^{prior}(x) * Pr_x(i)}{\int_0^1 f^{prior}(t) * Pr_t(i)\,\mathrm{d}t}$$

We define $d_i(x)$, distance of x to the domain of label i, as the absolute value of $\frac{(x-x_i^{sup})+(x-x_i^{inf})}{2}$, where $\{x_i^{inf}; x_i^{sup}\}$ are the lower and upper bounds of the dominance design-based interval defined in the previous section. K is the set of possible EPC grades $\{A; B; C; D; E; F; G\}$. The probability of having observed the label i given the energy quality rating x is then written:

$$Pr_x(i) = \frac{exp(-v * d_i(x))}{\sum_{k \in K} exp(-v * d_k(x))}$$

In the previous definition, v is a reliance level: the higher v, the most informative is EPC. For instance, if x belongs to the dominance interval of the label i $[x_i^{inf}; x_i^{sup}]$, then when v increases, $Pr_x(i)$ increases as well, and for any other label $j \neq i$, $Pr_x(j)$ decreases. In our simulation, we calibrate $v = 10$ to illustrate the Bayesian reading. Figure 4 represents resulting distributions.

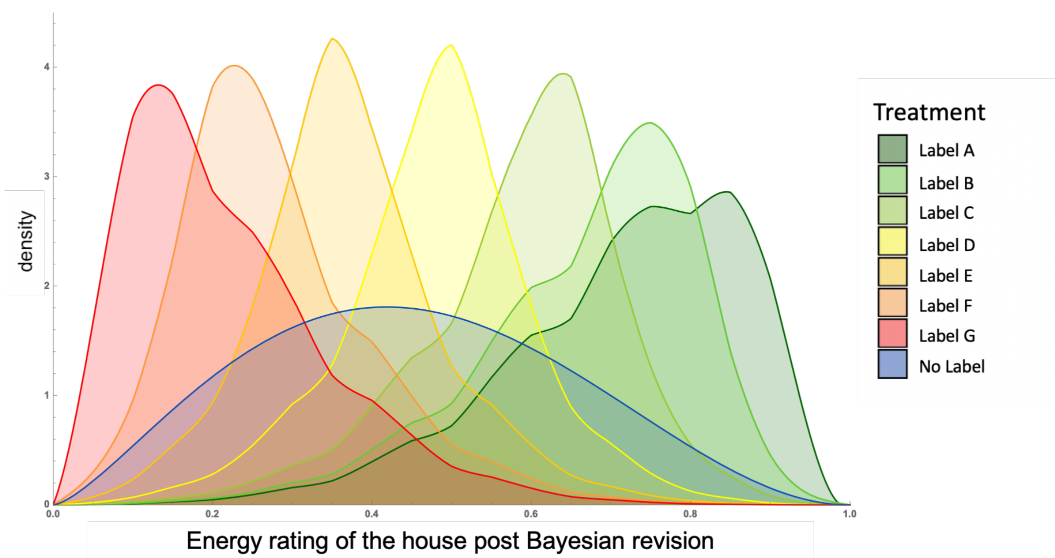


Figure 4: Simulations of ratings distributions based on a bayesian revision of prior beliefs

The blue curve (prior beliefs of subjects facing a no label ad) is modified into the colored ones according to the message received (EPC class, from A to G). Those counterfactual distributions are consistent with the ones empirically observed (see appendix A.2). Labels distort the prior beliefs, modes of the revised distributions are correctly ordered, following the logical hierarchy of labels. Moreover, this Bayesian inference gives rise to strongly skewed distributions as label's class gets more extreme, similarly to empirical distributions. The A-label reading stands out again: its mode is significantly lower than the ones of other labels, and the distribution is more disperse. This is explained by prior beliefs: even though they were only slightly shifted towards bad ratings compared to the scale center, this anchoring is sufficient to decrease substantially the informative power of the A-label. In accordance with our simulations results, we disprove conjecture 4 in result 4.

Result 4. *Conjecture 4 is not validated by experimental results: Energy Performance Certificate is not perceived as perfectly informative, subjects infer this information into their prior beliefs on house's energy efficiency.*

6 Conclusion

As far as we know, this is the first experimental study on the perception of houses energy performance. With a sample of 3,000 subjects representative of the French population, our protocol involved a control group and seven treatments to test the impact of Energy Performance Certificate on the perception of dwellings' energy quality. Our findings evidence that a significant part of the population, although still a minority, could be ignoring energy labels displayed on real estate adverts. Among socio-demographic characteristics, gender exhibits an unexpected influence on this diverse attention to energy labels, which can be explained by the specific design of energy performance certificates. On the other hand, we evidence an attention gap between tenants and owner-occupants. It could be explained by a "patrimonial value" vision of energy efficiency, rather than a "use value" spotlighted by the sponsors of thermal renovations, who usually emphasize expected savings on the energy bill.

We use a specific econometric strategy based on beta regressions to evidence the label impact. We show that the energy label is efficient and that its perception is consistent with the label design: each level of the energy certificate is perceived differently and gradually by the aggregated population. However it seems that EPC presents some characteristics of an experience good: we evidence that older subjects, more likely to have experienced real estate transactions with EPCs, tend to be more skeptic about the displayed information. The case of the top-level label, corresponding to low-consumption houses, shows up with a higher dispersion of subjects' judgements, which strengthens the hypothesis that the low credibility of EPC jeopardizes the emergence of a strong green value. Finally, we show that subjects cognitive reading of the EPC is mostly based on the deceptive design where label's grades seem to represent regular intervals of efficiency; however they do not consider that it is perfectly informative but more probably infer the signal into their prior beliefs on energy quality, suggesting that reading can be considered as bayesian.

This article approach is novel by treating information as continuous: subjects are neither perfectly informed or totally ignorant, they have a signal which is processed into usable information for the economic decision. We open the debate on the limits such a perception could cause to the green value of buildings: further research could focus on how to improve the design to transmit a more operational information, such as energy costs instead of primary energy consumption, and how to make EPCs more reliable.

Acknowledgments

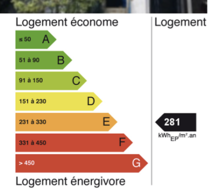
We would like to thanks the CSTB for providing fundings for this experiment. Moreover we thank helpful comments from Marc Baudry and from participants of the World Congress of Environmental and Resources Economists in Gothenburg (June 25-29, 2018), who awarded to this research the best poster price.

A Appendix

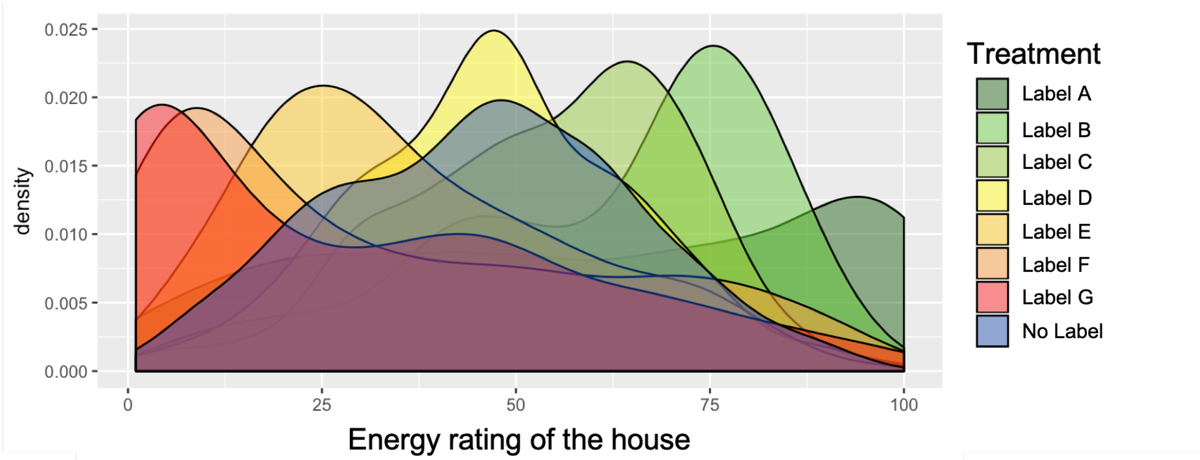
A.1 Real estate advert, Energy label E displayed

Maison 105 m^2, deux étages, 8 pièces, à proximité du centre-ville de Landerneau, 274 300 €

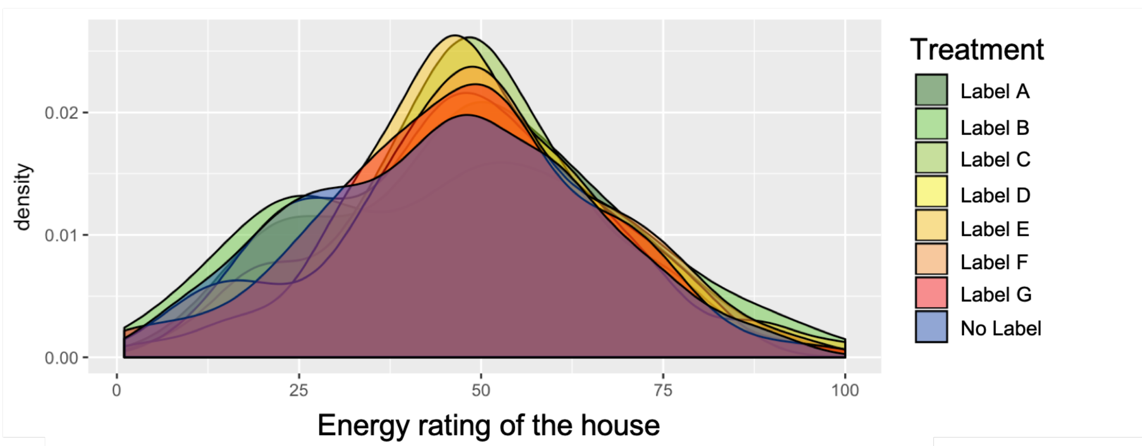
Charmante maison traditionnelle au rez-de-jardin donnant sur une ruelle piétonne. Belle pièce de vie lumineuse de 45 m^2, avec cheminée, exposée sud/ouest. Deux étages distribuant 4 chambres et 2 salles de bains avec WC séparés. Cuisine attenante entièrement équipée. Bureau à l'entresol. Huisseries alu double vitrage, chauffage au gaz. Garage et possibilité d'achat d'un terrain de 950 m^2.



A.2 Distributions of energy ratings, subjects attentive to energy labels (treatment groups) and subjects in the control group



A.3 Distributions of energy ratings, subjects inattentive to energy labels and subjects in control group



A.4 Tested variables

Table 7: Tested variables for econometric analyzes

Label
Age
Gender
Income
Education level
Socio-economic status
Region
Climate indicator
Owner-occupant/Tenant status
Household size
Number of real estate transactions achieved
Housing search after EPC introduction
Individual/Collective heating status
Heating energy
Dwelling's area

References

Akerlof, G. A. (1970). The market for "lemons": Quality uncertainty and the market mechanism. *The quarterly journal of economics*, 488–500.

Andor, M., A. Gerster, and S. Sommer (2016). Consumer inattention, heuristic thinking and the role of energy labels.

Baksi, S., P. Bose, and D. Xiang (2017). Credence goods, misleading labels, and quality differentiation. *Environmental and Resource Economics 68*(2), 377–396.

Ben Youssef, A. and C. Abderrazak (2009). Multiplicity of eco-labels, competition, and the environment. *Journal of agricultural & food industrial organization 7*(2).

Brécard, D. (2014). Consumer confusion over the profusion of eco-labels: Lessons from a double differentiation model. *Resource and energy economics 37*, 64–84.

Brécard, D. (2017). Consumer misperception of eco-labels, green market structure and welfare. *Journal of Regulatory Economics 51*(3), 340–364.

Brécard, D., B. Hlaimi, S. Lucas, Y. Perraudeau, and F. Salladarré (2009). Determinants of demand for green products: An application to eco-label demand for fish in europe. *Ecological economics 69*(1), 115–125.

Brounen, D. and N. Kok (2011). On the economics of energy labels in the housing market. *Journal of Environmental Economics and Management 62*(2), 166–179.

Cason, T. N. and L. Gangadharan (2002). Environmental labeling and incomplete consumer information in laboratory markets. *Journal of Environmental Economics and Management 43*(1), 113–134.

Chang, C. (2007). The relative effectiveness of comparative and noncomparative advertising: Evidence for gender differences in information-processing strategies. *Journal of Advertising 36*(1), 21–35.

Collado, R. R. and M. T. S. Díaz (2017). Analysis of energy end-use efficiency policy in spain. *Energy Policy 101*, 436–446.

Cribari-Neto, F. and A. Zeileis (2010). Beta regression in r. *Journal of Statistical Software 34*(2), 1–24.

Crosetto, P., L. Muller, and B. Ruffieux (2016). Helping consumers with a front-of-pack label: Numbers or colors?: Experimental comparison between guideline daily amount and traffic light in a diet-building exercise. *Journal of Economic Psychology 55*, 30–50.

Darley, W. K. and R. E. Smith (1995). Gender differences in information processing strategies: An empirical test of the selectivity model in advertising response. *Journal of advertising 24*(1), 41–56.

Enax, L., I. Krajbich, and B. Weber (2016). Salient nutrition labels increase the integration of health attributes in food decision-making. *Judgment and Decision Making 11*(5), 460.

Espinheira, P. L., S. L. Ferrari, and F. Cribari-Neto (2008). On beta regression residuals. *Journal of Applied Statistics 35*(4), 407–419.

European Commission, D.-G. f. E. (2017, November). European union energy in figures, statistical pocketbook 2017.

Ferrari, S. and F. Cribari-Neto (2004). Beta regression for modelling rates and proportions. *Journal of Applied Statistics 31*(7), 799–815.

Fuerst, F. and P. McAllister (2011). Green noise or green value? measuring the effects of environmental certification on office values. *Real Estate Economics 39*(1), 45–69.

Fuerst, F., P. McAllister, A. Nanda, and P. Wyatt (2015). Does energy efficiency matter to home-buyers? an investigation of epc ratings and transaction prices in england. *Energy Economics 48*, 145–156.

Gillingham, K., M. Harding, and D. Rapson (2012). Split incentives in residential energy consumption. *The Energy Journal*, 37–62.

Harrison, G. W. and J. A. List (2004). Field experiments. *Journal of Economic literature 42*(4), 1009–1055.

Hodgkins, C., J. Barnett, G. Wasowicz-Kirylo, M. Stysko-Kunkowska, Y. Gulcan, Y. Kustepeli, S. Akgungor, G. Chryssochoidis, L. Fernández-Celemin, S. S. genannt Bonsmann, et al. (2012). Understanding how consumers categorise nutritional labels: a consumer derived typology for front-of-pack nutrition labelling. *Appetite 59*(3), 806–817.

Houde, S. (2018). How consumers respond to product certification and the value of energy information. *The RAND Journal of Economics 49*(2), 453–477.

Hyland, M., R. C. Lyons, and S. Lyons (2013). The value of domestic building energy efficiency? evidence from ireland. *Energy Economics 40*, 943–952.

Insee (2018). Bilan démographique 2017. *Insee Première 1683*.

Jaffe, A. B. and R. N. Stavins (1994). The energy-efficiency gap what does it mean? *Energy policy 22*(10), 804–810.

Kahn, M. E. and N. Kok (2014). The capitalization of green labels in the california housing market. *Regional Science and Urban Economics 47*, 25–34.

Kahneman, D. (2003). Maps of bounded rationality: Psychology for behavioral economics. *The American economic review 93*(5), 1449–1475.

Kern, F., P. Kivimaa, and M. Martiskainen (2017). Policy packaging or policy patching? the development of complex energy efficiency policy mixes. *Energy Research & Social Science 23*, 11–25.

Kulsum, A. (2012). *Getting to Green-A Sourcebook of Pollution Management Policy Tools for Growth and Competitiveness.* World Bank Group.

Lacetera, N., D. G. Pope, and J. R. Sydnor (2012). Heuristic thinking and limited attention in the car market. *The American Economic Review 102*(5), 2206–2236.

LaVoie, N. R., B. L. Quick, J. M. Riles, and N. J. Lambert (2017). Are graphic cigarette warning labels an effective message strategy? a test of psychological reactance theory and source appraisal. *Communication Research 44*(3), 416–436.

Meyers-Levy, J. (1986). *Gender differences in information processing: A selectivity interpretation.* Ph. D. thesis, Northwestern University.

Meyers-Levy, J. (1994). *Gender differences in cortical organization: Social and biochemical antecedents and advertising consequences.* Hillsdale, NJ: Erlbaum.

Meyers-Levy, J. and B. Loken (2015). Revisiting gender differences: What we know and what lies ahead. *Journal of Consumer Psychology 25*(1), 129–149.

Meyers-Levy, J. and D. Maheswaran (1991). Exploring differences in males' and females' processing strategies. *Journal of Consumer Research 18*(1), 63–70.

Miller, G. F., S. Gupta, J. D. Kropp, K. A. Grogan, and A. Mathews (2016). The effects of pre-ordering and behavioral nudges on national school lunch program participants? food item selection. *Journal of Economic Psychology 55*, 4–16.

Min, J., I. L. Azevedo, J. Michalek, and W. B. de Bruin (2014). Labeling energy cost on light bulbs lowers implicit discount rates. *Ecological Economics 97*, 42–50.

Miquel, M.-J., E.-M. Caplliure, C. Pérez, and E. Bigné (2017). Buying private label in durables: Gender and other psychological variables. *Journal of Retailing and Consumer Services 34*, 349–357.

Muller, L. and M. Prevost (2016). What cognitive sciences have to say about the impacts of nutritional labelling formats. *Journal of Economic Psychology 55*, 17–29.

Olaussen, J. O., A. Oust, and J. T. Solstad (2017). Energy performance certificates–informing the informed or the indifferent? *Energy Policy 111*, 246–254.

Olsen, M. E. (1983). Public acceptance of consumer energy conservation strategies. *Journal of Economic Psychology 4*(1-2), 183–196.

Panzone, L., D. Hilton, L. Sale, and D. Cohen (2016). Socio-demographics, implicit attitudes, explicit attitudes, and sustainable consumption in supermarket shopping. *Journal of Economic Psychology 55*, 77–95.

Putrevu, S. (2001). Exploring the origins and information processing differences between men and women: Implications for advertisers. *Academy of marketing science review 2001*, 1.

Putrevu, S., J. Tan, and K. R. Lord (2004). Consumer responses to complex advertisements: The moderating role of need for cognition, knowledge, and gender. *Journal of Current Issues & Research in Advertising 26*(1), 9–24.

Ramos, A., A. Gago, X. Labandeira, and P. Linares (2015). The role of information for energy efficiency in the residential sector. *Energy Economics 52*, S17–S29.

Santarius, T. and M. Soland (2018). How technological efficiency improvements change consumer preferences: Towards a psychological theory of rebound effects. *Ecological Economics 146*, 414–424.

Santos, R., P. Antunes, G. Baptista, P. Mateus, and L. Madruga (2006). Stakeholder participation in the design of environmental policy mixes. *Ecological economics 60*(1), 100–110.

Sardianou, E. (2007). Estimating energy conservation patterns of greek households. *Energy Policy 35*(7), 3778–3791.

Schley, D. R. and M. L. DeKay (2015). Cognitive accessibility in judgments of household energy consumption. *Journal of Environmental Psychology 43*, 30–41.

Shewmake, S., A. Okrent, L. Thabrew, and M. Vandenbergh (2015). Predicting consumer demand responses to carbon labels. *Ecological Economics 119*, 168–180.

Simas, A. B., W. Barreto-Souza, and A. V. Rocha (2010). Improved estimators for a general class of beta regression models. *Computational Statistics & Data Analysis 54*(2), 348–366.

Stadelmann, M. and R. Schubert (2018). How do different designs of energy labels influence purchases of household appliances? a field study in switzerland. *Ecological Economics 144*, 112–123.

Stavins, R. N. (2003). Experience with market-based environmental policy instruments. *Handbook of environmental economics 1*, 355–435.

Steiner, B., A. Peschel, and C. Grebitus (2017). Multi-product category choices labeled for ecological footprints: Exploring psychographics and evolved psychological biases for characterizing latent consumer classes. *Ecological Economics 140*, 251–264.

Teisl, M. F., J. Rubin, and C. L. Noblet (2008). Non-dirty dancing? interactions between eco-labels and consumers. *Journal of Economic Psychology 29*(2), 140–159.

Tinbergen, J. (1952). *On the theory of economic policy.* Amsterdam: North Holland.

UFC (2017, September). Diagnostics de performance énergétique: Stop à la loterie ! *Que Choisir*.

Verplanken, B. and M. W. Weenig (1993). Graphical energy labels and consumers' decisions about home appliances: A process tracing approach. *Journal of Economic Psychology 14*(4), 739–752.

Waechter, S., B. Sütterlin, J. Borghoff, and M. Siegrist (2016). Letters, signs, and colors: How the display of energy-efficiency information influences consumer assessments of products. *Energy Research & Social Science 15*, 86–95.

Wolin, L. D. (2003). Gender issues in advertising?an oversight synthesis of research: 1970–2002. *Journal of advertising research 43*(1), 111–129.