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WORKING PAPER

GREEN, YELLOW OR RED LEMONS?

Artefactual field experiment on houses energy labels perception

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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 looked as their ability to shift behaviors, whereas their first goal is to enable people to discriminate labelled goods. This paper studies how the complex information displayed by houses' Energy Performance Certificates 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. Unexpectedly, we find out that gender is the most critical socio-demographic characteristic in this changing attention. We interpret this effect by the Selectivity Hypothesis: energy labels design engages more male subjects.

Among attentive subjects, energy labels' efficiency to transmit information is mixed. Subjects do identify separately each label's grade, but their judgment is biased by prior beliefs and blurred by idiosyncratic features. Aggregated reading is Bayesian: subjects infer the label information to revise their belief on energy quality. Moreover, our results shed light on strong asymmetries. While worsening grades induce decreasing judgments on energy quality, top level quality label seems to undergo skepticism, intensifying idiosyncratic noise.

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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 (see 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 Certificates. This is key in the real estate sector, as buildings account for 39% of Europe final energy consumption, and even slightly more in France, where they reach 42% of the country final energy consumption (European Commission (2017)).

Following a European directive, the French law imposes since 2007 to display the Energy Performance Certificate (designated as EPC or energy label in the present article), in every real estate advert. 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 France. Firstly its effect on prices is disputed. 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 there is not until now any academic study aiming at understanding how houses energy labels are 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, prerequisite to the emergence of a green value. 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 one steady 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 this label, depending on gender and landowner/tenant status. Moreover, people's perception of energy quality is asymmetric regarding label's grades, which prevents a clear-cut differentiation of green buildings. We find out that age and experience with the real estate market engenders skepticism towards EPCs. Section five concludes with our main findings.

2 Literature review: labels efficiency

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 today used 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. Last ones include information programs as labeling. 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 (see on the energy efficiency issue 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 behavioral limits of labels. First, papers modeling the presence of multiple eco-labels (see Ben Youssef and Abderrazak (2009) Brécard (2014), Baksi et al. (2017) and Brécard (2017)) forebode limits in consumers' ability to discriminate different labels' qualities. They underline the need of 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 others 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 choices among treated students compared to the control group.

In this context, labels role is twofold: providing information to consumers and inducing specific intuitions. Labels design have then to be relevant to both convey information and set up in good heuristics; 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. 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 labels impact 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 importance of people's characteristics and cognitive salience to have an efficient label. However these conclusions should not be directly transmitted to 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.

2.3 Energy labels

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 been studied when used for home appliances: freezers, 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. Field study conducted by Stadelmann and Schubert (2018) tests the effect of different label designs on purchases of household appliances, 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 real 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 today's EU design of energy labels for these products. However this small 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), Brounen and Kok (2011), Hyland et al. (2013), Kahn and Kok (2014), Fuerst et al. (2015), Ramos et al. (2015)), but their results are contrasted and 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 houses' ones. 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. *Energy Performance Certificate perception varies according to socio-demographic characteristics of 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 discussed by consumers associations. As academic literature exhibits the role of prior beliefs in the relation to labels, we formulate the conjecture 2.

Conjecture 2. *Energy Performance Certificates perception is biased by subjects' prior beliefs.*

The literature which investigates buildings' "green value" systematically represents the EPC as a dummy in their hedonic models. This modeling choice relies on the assumption that information displayed by Energy Performance Certificates is perceived as perfect by households: we want to test this assumption, formulated in the conjecture 3.

Conjecture 3. *Energy Performance Certificates are perceived by subjects as perfect information on houses energy quality.*

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 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.

Protocol was chosen to fit French housing market context: in France, almost 90% of people peruse real estate adverts online (Lefebvre (2015)). 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 is then split into 5 steps. In the first step, experiment presented randomly one out of eight real estate adverts to the subject. All adverts presented the exact same house, and only differed by the energy performance certificate. 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 few moments 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.

Experiment second step consisted in questions about the general informations 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 of 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.

Fifth step of the experiment consisted in several questions to evaluate subjects experience of

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

real estate market and on houses energy performance. Socio-demographic questions were also included 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 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 three parts. First one describes data through box-plots and density distributions of energy ratings for each treatment. The Kolmogorov-Smirnov test is applied to pairs of ratings distributions to evaluate if perception of various grades is significantly different.

In a second part, we investigate the determinants of being attentive to the EPC. Similar statistical tests are applied to subjects who declared, in the fourth step of 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.

In a third part, we analyze energy quality perception within two groups of subjects. First group gathers subjects who were not exposed to the energy label, *i.e.* the control group. Second group is a subset of subjects who received a treatment: it gathers subjects who 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 beta regressions by ascendant stepwise analysis on the two groups previously described (control group vs attentive subjects).

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, 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.

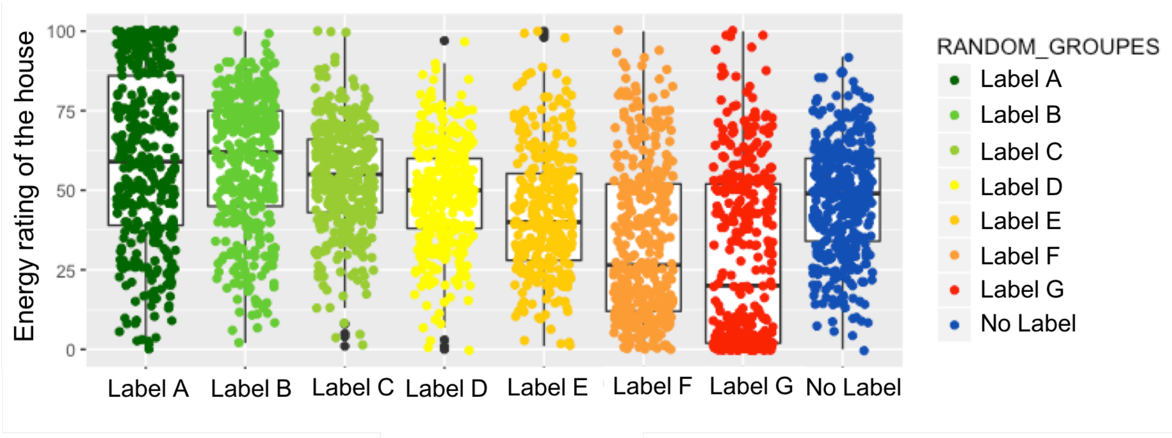

Figure 1: Box-plots of energy ratings

On figure 2 we draw the probability densities of energy ratings. Three main features can be drawn from these distributions. First, we can observe that distributions' modes are correctly ordered: they are higher from label G to label A, and 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 the various distributions (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.

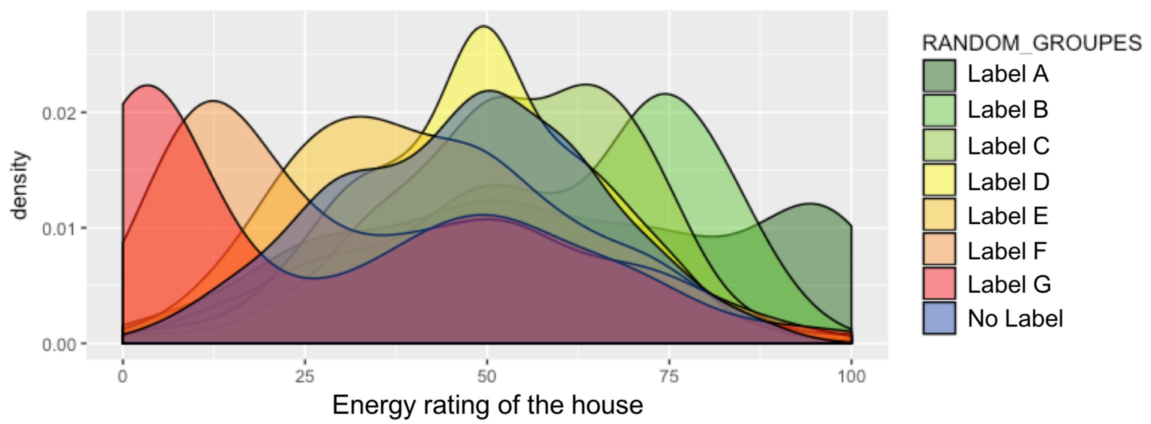

Figure 2: Distributions of energy ratings, all subjects

4.1.2 Statistical tests

As descriptive data underline that all distributions overlap, and that several distributions have almost the same means and similar modes, a legitimate question arises: are these distributions significantly different? In order to answer it, we use the nonparametric test Kolmogorov-Smirnov. Results shown in table 1 exhibit at the level of 1% that all energy ratings distributions drawn from the treatments are significantly different. However distribution derived from treatment "label D" is not significantly different from the control group.

Table 1: Significance of the difference between distributions

	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	0.0759
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. Once noted that each label was perceived differently, and before testing the strengths of these labels impact on the perception of energy performance, we investigate the determinants of subjects' attention to the Energy Performance Certificate.

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 these people ratings, we replicate on the subset of these subjects the analysis of the previous section (see appendix A.3 for the corresponding distributions). In table 2, 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 similar to the ones of control group.

Table 2: 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 significance with a level of confidence of 90% or higher. Coefficients of the model can be found in table 3.

Table 3: Determinants of the attention to the energy label

	Binary dependent variable:
	Attention to the Energy Label
Gender: Woman	$-\mathbf{0.292}^{***}$
	(0.055)
Landowner	$\mathbf{0.157}^{***}$
	(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 are significant to the energy labels' attention: gender, landowner-tenant status, the fact of having or not being involved in a housing search since the introduction of EPC, and the region where lives the subject. Attention should be paid firstly to factors which appear not being significant: 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 significant, 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 on market's tightness, 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.

The effect of the landowner status, in comparison to the tenant status, is interesting and significant at a level of 1% type I error: subjects being landowners were more attentive to the energy label. However, in France, no matter if you are a tenant or a landowner, you have to pay for the energy bill of the dwelling you are living in. This effect advocates for a "patrimonial value" vision of energy efficiency for French households rather than a "use value" vision.

The most significant variable is not one of those previously mentioned, but 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, like in ethics, risk-aversion, trust, competitiveness and pro-environmental behaviors. 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 self-evident. 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. We base our analysis on 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 (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 (see experiments described in the papers of Meyers-Levy and Maheswaran (1991), Meyers-Levy (1994), Darley and Smith (1995), Miquel et al. (2017), and 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 informations have 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 informations 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 and then males will tend to select more that kind of information. Secondly, the information design is directed to 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 (see 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 (see Putrevu et al. (2004)); furthermore, this technical information is poorly handy in itself, as its traduction 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 confirm conjecture 1.

Result 1. *Conjecture 1 is supported by our experiment: socio-demographic characteristics affect attention to the Energy Performance Certificate.*

4.3 Econometric analysis of labels reading

Beyond the attention to this informational tool, we want to analyze how subjects' cognitive systems "digest" it once they have accepted this information. In order to understand energy labels reading by subjects attentive to them, we use an econometric strategy based on beta regressions. Both the fact that energy efficiency ratings were confined in a finite interval and the skewness of labels' ratings distribution justify this approach. In the subsection 4.3.1 we detail this strategy, while the subsection 4.3.2 presents the results of our regressions.

4.3.1 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 mean and variance of a beta distributions 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.

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

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

A strength of these beta-regressions is that parameters μ and Φ could be explained by different sets of regressors. We use two regressions that follow the same α and β values that describe the distribution, and obtain then two different models associated to each parameter μ and Φ. In the first regression, we focus on the mean, assuming the precision parameter constant. In the second regression, mean is assumed constant and we analyze the factors affecting the precision parameter. That strategy enables to correct the heteroskedasticity issues intrinsic to the beta distributions. Estimators (see contributions by Espinheira et al. (2008) and Simas et al. (2010)) 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. 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 the table 6 (see appendix A.4).

4.3.2 Energy labels perception

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 control group. Two variables exhibit significant impact 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: the reference case being baccalaureate, subjects with the highest level of education tend to rate lower 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 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 lower their rating of the energy quality of the house compared to average subjects. 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 normal distribution of energy performance ratings made by subjects in the control group (see appendix A.3). This heterogeneity in ratings does not result from systematical bias but from idiosyncratic reading of the real estate ad: each subject perceives differently the various elements (as the pictures and informations about heating system and windows) and infer them differently according to their prior beliefs.

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	

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 3 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 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 of 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. Inverse Mills ratio doesn't exhibit significance at common levels, we reject then the hypothesis of a sample selectivity effect. Analysis of these regressions is threefold: houses energy labels reading is unbiased and consistent with the design, but the generation most exposed to this label might be more skeptic. Moreover, label A perception is specific, subjects relying more on other informations when facing this peculiar category of energy labels.

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, labels are efficient in making subjects' perception unbiased. Variables which were influencing the mean of energy ratings for subjects in the control group (see table 4) are cleared out for informed subjects; indeed in table 5, education level and climate show no influence on people 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 models' coefficients, results confirm main useful insights drawn from the previous section. As labels worsen, the mean of energy ratings decreases, while upgrading labels increases energy ratings. Moreover, when labels become more extreme, whereas they turn greener or redder, the precision of energy ratings lower. 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. We can then interpret energy labels reading as Bayesian: subjects interpret the energy label as an approximative signal of house's energy performance, and use it when assessing the energy performance of dwellings.

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 a landowner 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 (see the fourth study "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, highlighting the key role of prior beliefs. The negative effect of the variable "Housing search after EPC introduction" strengthens this explanation. The appearance of these variables for the treated subjects, facing an EPC, whereas they had no impact on ratings made by subjects in the control group, evidence a specific effect of prior beliefs on EPC reading, stated in result 2.

Result 2. *Conjecture 2 is supported by our experiment: prior beliefs bias Energy Performance Certificate reading.*

Third lesson from our econometric analysis comes from coefficients analysis. In table 5, coefficients point out a specific perception 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. Several elements can explain this dispersion: firstly A-labelled houses are not common in the French real estate market, which may raise skepticism among subjects when they see this specific label. Secondly, label A is supposed to indicate extremely efficient houses: subjects might then be using more complementary informations to validate this label, inducing a stronger dispersion due to idiosyncratic characteristics of subjects, and in our experiment divergent informations are given by the real estate ad. In both cases, this result demonstrates that energy labels are not perceived as perfect information by subjects: they rely on other clues and idiosyncratic features to build their judgment on the energy quality of the house, and this invalidates the conjecture 3 made by usual hedonic analysis.

Result 3. *Conjecture 3 is not supported by data: Energy Performance Certificates are not perceived as perfect signals on house energy quality. Subjects reading is Bayesian: they infer EPC information to revise their belief on energy quality.*

Reasons driving this "distrust" in top label are not self-evident and still have to be investigated in further research. It is an important result when addressing the question of buildings' green value: if households do not perceive A-labelled houses as more performant than B-labelled houses, then it prevents most efficient houses from increasing their market price and the green value is capped below its full potential.

5 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 the various categories of EPC on the perception of houses energy quality. Our findings evidence that a significant part of the population, although 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.

We use a specific econometric strategy based on beta regressions to understand labels reading. We show that perception is bayesian due to idiosyncratic features and not biased by socio-demographic characteristics. Perception is consistent with the label design: each level of the energy certificate is perceived differently and gradually by the aggregated population. However prior beliefs interfere with the label information: we evidence that age and prior experiences with EPC tend to lower perceived quality of this signal. 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 green value.

This article approach is novel by treating information as continuous: subjects are not 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 typical thermodynamic consumption, how to make EPCs more reliable and highlight the top quality label.

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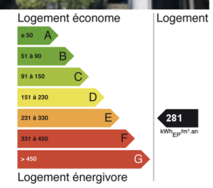
A Appendix

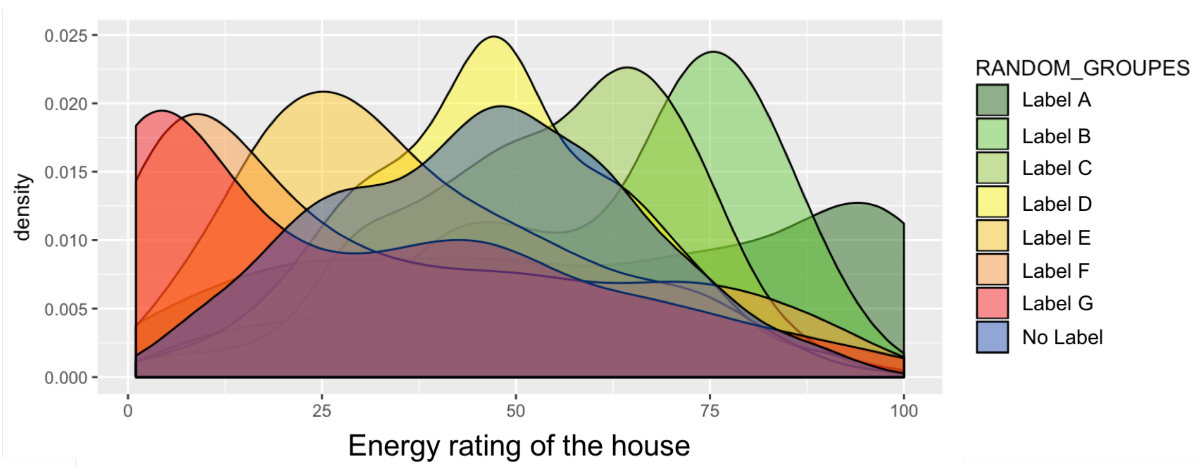
A.1 Real estate advert, Energy label E displayed

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

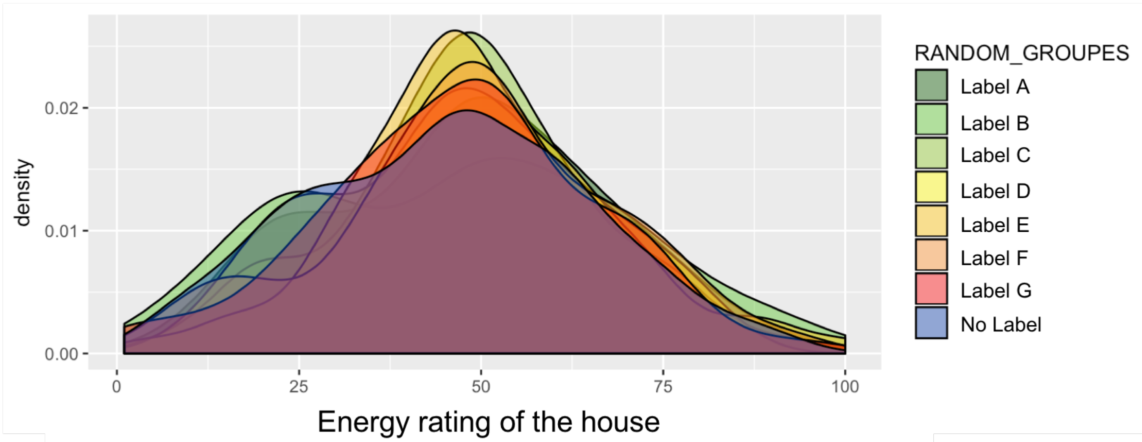
Charmante maison traditionnelle au rez-de-jardin donnant sur une ruelle piétonne. Belle pièce de vie lumineuse de 45 m^2, avec cheminée, exposée sud/ouest. Deux étages distribuant 4 chambres et 2 salles de bains avec WC séparés. Cuisine attenante entièrement équipée. Bureau à l'entresol. Huisseries alu 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 and subjects in control group



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



A.4 Tested variables

Table 6: Tested variables for econometric analyzes

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

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