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Green, yellow or red lemons?

Framed field experiment on houses energy labels perception.

(Working Paper - First Draft)

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 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 framed 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 take heed of the energy label. Unexpectedly, we find out that gender is the most differentiating characteristic in this changing sensitivity to energy performance certificates. We interpret this effect by the Selectivity Hypothesis: energy labels design engages more male subjects.

Among sensitive subjects, energy labels' efficiency to transmit information is mixed, as our results indicate a Bayesian reading of houses energy labels. Subjects identify separately each label's grades, and their perception is not systematically biased by individual characteristics, but idiosyncratic features blur their judgment. Moreover, this perception exhibits strong asymmetries. While worsening grades induce decreasing judgments, upgrading label's class do not strongly enhance people's evaluation of energy quality: on the contrary, top level quality label seems to undergo skepticism and intensifies idiosyncratic noise.

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, due to informational asymmetries. Half a decade later, this issue is newsworthy as information failures on products' quality plague the development of eco-friendly consumption (Cason and Gangadharan (2002)). In order to address this question, labels and certificates use has increased sharply. In the wake of pioneer researchers as Daniel Kahneman, Amos Tversky, Richard Thaler and Cass Sunstein, who ushered the new field of behavioral economics, labels have become a very popular tool to influence people's behavior, and key to many environmental policies (Kulsum (2012)). Labels are widely used in the food sector, to promote organic food, products with a low carbon footprint, or farmers respectful of the environment.

Energy performance certificates also spread, in a much more compelling framework: in the European Union, a unified design has to be displayed on home appliances such as refrigerators, on vehicles but also on buildings to inform consumers on goods' energy performance. This mandatory certification of energy-consuming goods is an answer to the energy-efficiency gap identified by Jaffe and Stavins (1994). This gap, partly due to information imperfection and asymmetry, is especially challenging in the residential and tertiary sector. Buildings account for 39% of final energy consumption in Europe, and even slightly more in France, where they reach 42% of the country final energy consumption (European Commission (2017)).

In order to develop thermal renovation of buildings, the French law imposes since 2007 to display the Energy Performance Certificate (designated as EPC or energy labels in the present article), in every real estate ad or transaction. This is the transposition in the French law of the Energy Performance Certificates. 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. If the EPC reduces information asymmetry between buyers and sellers, it suffers from several weaknesses. First one is its specific design: using colors, letters and arrows of different sizes, it aims at inducing a heuristic judgment, while the intrinsic information it is based on is a complex expert knowledge - the estimated average primary energy consumption in kWh per meter-squared and per year. Second weakness of the EPC is its poor reliability, as this indicator is not a measure. 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. Psychological salience and technical seriousness 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 the energy performance certificate is an efficient tool to enable households to differentiate real estates according to their energy quality. In the second section we review the academic works interested in labels efficiency: while a growing number of studies focus on labels' efficiency to induce a shift in agents' behaviors, this review underlines a lack in the understanding of the cognitive processes at work when households face an energy label. The third section describes our experimental design: we present various energy performance certificates to 3,000 French individuals in a randomized experiment. Results are presented in the fourth section: french population is unequally sensitive to this label, and people's perception of energy performance certificates is asymmetric and imperfect, which prevents a clear-cut differentiation of green buildings. We investigate in this section the role of individual characteristics, key to labels' sensitivity but successfully obliterated by labels' perusal. 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 ecolabels (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: 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 obviously depend on the amount of others information they have to process and on the timing 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 demonstrate that both an incentive to use the reasoning system, by pre-ordering, and an incentive to guide intuition, a nudge, can significantly improve a healthy diet.

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 design is so paramount to their efficiency. Indeed, 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) build a psycho-economic model of consumers reactions which points out the importance of "well-designed labeling practices as they significantly impact individuals' perceptions".

2.2 Food labels

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 individual 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 of cognitive salience to have an efficient label. It is important to keep these features in mind for our research question; 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 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.

3 Experiment, data and empirical methods

3.1 Experimental design

In order to measure energy labels impact on households' perception of energy performance, a standardized questionnaire was developed and administrated through an online survey on a sample of 3,000 French citizens, representative of the French population. Questionnaire was tuned with pre-tests, firstly with thorough interviews with a limited number of subjects, then with a first questionnaire online with 300 participants. If we refer to the classification made by Harrison and List (2004), our experiment can be described as a framed field experiment: subjects know they are in a experiment, information given to them is contextualized, and the subject pool is a representative sample of the French population.

Methodology of the expriment was chosen in order to fit the context in which French people face houses energy labels. First, online administration is adequate as the French housing market is heavily reliant on the web: almost 90% of French people use it to see real estate adverts (Lefebvre (2015)). Second, testing the influence of energy labels on real estate adverts is relevant as the law imposes to sellers to display them since 2007; there is only one other time when the energy label will be specified, at the signature of the contract, after the potential buyer bids for the house. The key moment where energy labels can have an impact on people's perception and before the decision of making a bid for a house or a flat is then precisely when they see the real estate adverts, on the web.

After preliminary questions about age, location and gender to set quotas, the questionnaire started with a welcoming message announcing that people were participating to a survey on the real estate market and a warning specifying that once an answer is validated, they will not be able to go back to the question. This preliminary message did not mention that survey's topic was energy labels. Questionnaire is then split into 8 sections, with a total of 38 questions. The first questionnaire section presented randomly one of eight real estate adverts: one control and seven treatments. Adverts all presented the same house, and only differed by the energy EPC they displayed. Real estate advert was built as a typical french house ad[1]. Each participant was randomly presented one advert among the eight. Control ad did not display any energy label, while treatment ads displayed the official energy performance certificate; each treatment indicated one of the seven categories of energy labels, from A to G. Instruction above this real estate ad 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. An example of these real estate ads can be found in appendix A.1.

[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.

The second questionnaire section consisted in two questions about the general informations displayed on the real estate ad, to observe which characteristics were more minded by participants. In the third questionnaire section, 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 variable studied in the paper. In the following question participants were asked which was the energy performance expressed by the energy label. Fourth questionnaire section consisted in several questions to evaluate subject experience of the real estate market and of houses energy performance, while the fifth questionnaire section asked to the subject on which criteria they evaluate the energy expenditures of housing. Sixth questionnaire section investigates subject knowledge and perception of the "energy label" as a public policy tool, seventh questionnaire section was made of questions to give an "energy-ecological characterization" of the participant. Eighth questionnaire section closed the questionnaire with socio-demographic questions.

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. 2,183 respondents completed the questionnaire on their computer, 601 did it on their smartphone and 216 on their tablet.

Our main dependent variable is subjects' rating of house's energy performance. Data analysis consists of three parts. First, in a general description of data, we visualize the impact of energy labels through boxplots and a representation of energy ratings' distributions according to the energy label presented to subjects. To determine if energy labels have an impact on people's perception of energy performance, and if this impact differs from a class to the other one, several statistical tests are applied to each label ratings' distribution. Shapiro-Wilk test is used to assess the normality of distributions. The Kolmogorov-Smirnov test is applied to pairs of distribution to evaluate if perception of varied classes is significantly different.

In a second step, we investigate the determinants of energy labels' receptiveness. Statistical tests similar to those used in the previous part of data analysis. Then an econometric model based on a logistic regression is built using an ascendant stepwise method of optimization based on the Akaike Information Criterion.

In a third step, we separate subjects in two groups. First group gathers subjects who either were not exposed to the energy label or were not receptive to it (*i.e.* virgin subjects). Second group gathers ratings made by subjects who were exposed and sensitive to the energy label (*i.e.* informed subjects). In order to take into account the fact that ratings are constrained in the interval [0,100], and the intrinsic heteroscedasticity that derives from this condition, we build an econometric model based on beta distributions. This method enables a double analysis, on the determinants of distributions' both means and dispersions. We implement this beta regression by an ascendant stepwise analysis on the two groups of data previously described (virgin vs informed subjects).

4 Results

4.1 Data overview

4.1.1 Descriptive data

On figure 1, we represent energy ratings' boxplots for the control group (real estate ad with no energy label) and the seven treatments (real estate ads with energy label of different categories). At first sight, we can see that, while labels are getting extremely positive (resp. negative), ratings distributions shift towards good levels (resp. bad levels). In both ways, boxplots' width increases when the gap between the label and the central label D increases. Moreover, energy ratings of the control group a median close to the center of the scale, just like energy ratings of subjects who faced the central label D. This is a good sign that our real estate ad did not in itself shift judgments on energy efficiency of the house. If medians are globally correctly ordered, there is an tiny inversion between Label A and Label B. It seems also that Label G ratings are much more concentrated on the inferior boundary of our scale than Label A ratings are on the superior boundary.

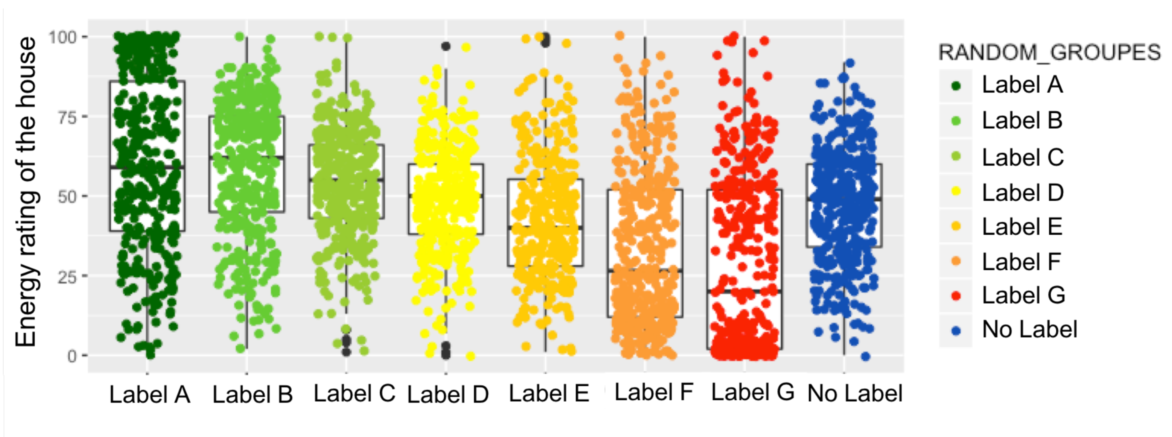

Figure 1: Boxplots of energy ratings

On figure 2 we draw the probability densities of energy ratings; groups of subjects differ by the energy label that was presented to them. Three main features can be drawn from these distributions. First, we can observe that various 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": 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 second question in the second section of our test, 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 did not notice any energy label instead one was present on the advert; a similar number of subjects did not notice the energy label 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, this second mode 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 is a distribution centered in the middle of the scale.

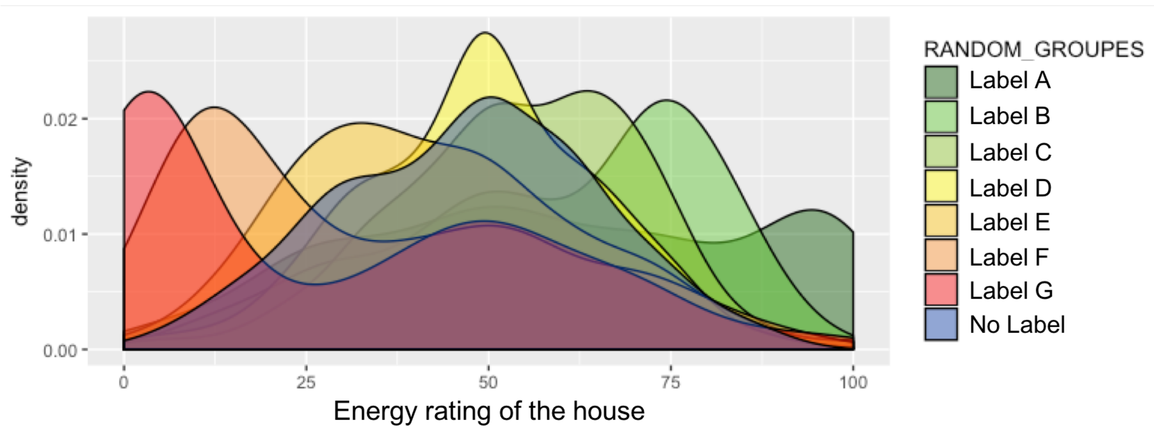

Figure 2: Distributions of energy ratings, all subjects

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 apply two different tests: first the Shapiro-Wilk test to determine if distributions are normal. Results (table 1) show that groups with labels A, B, C, E, F, G exhibit non-normal distributions, with strong significance levels (above 99%). However, for the control group and the group which received the treatment label D, which is the central treatment, we cannot reject the hypothesis of normality of distributions. For treatment groups, we conjecture that beta distributions would better fit the energy ratings, and the econometric analysis in section 4.3 will take it into account.

Table 1: Normality distributions tests

	Shapiro-Wilk test
	W statistic
Label A	0.9288***
Label B	0.9321***
Label C	0.9852***
Label D	0.9948
Label E	0.968***
Label F	0.8793***
Label G	0.7906***
No Label	0.9933
Note:	*p<0.1; **p<0.05; ***p<0.01

As specified in previous section on descriptive data, it is necessary to test which in those distributions are significantly different. Given that they are not normal, we use the nonparametric test Kolmogorov-Smirnov. Results shown in table 2 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 2: 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 houses energy label induces a significantly different perception in the population. Label A is perceived differently from label B, which is perceived differently from label C, etc. Nevertheless, label D does not induce a significantly different perception from 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 want to to investigate the determinants of subjects' sensitivity to the Energy Performance Certificate.

4.2 Determinants of sensitivity 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 second question of the thierd section of the questionnaire. One quarter of them declared not remembering the energy label which was displayed on their advert. In order to test if energy labels had an unconscious impact on these people ratings of energy efficiency, we replicate on the subset of these subjects the analysis of the previous section (see appendix A.3 for the corresponding distributions). In table 3 we can see that we cannot reject the normality hypothesis. In table 4, the Kolmogorov-Smirnov test moreover 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. Those 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 rating of the house is unbiased by the energy label, and is similar to the one of subjects in the control group.

Table 3: Normality of distributions for subjects insensitive to energy labels

	Shapiro-Wilk test
	W statistic
Label A insensitive	0.9828
Label B insensitive	0.9801
Label C insensitive	0.9853
Label D insensitive	0.9802
Label E insensitive	0.9736
Label F insensitive	0.9774
Label G insensitive	0.9881
No Label	0.9933
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 4: Labels induced no significant difference between ratings of insensitive 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 would be to estimate if some individual characteristics of subjects have an impact on the probability of being sensitive to the energy label (*i.e.* taking heed of the label on the ad). To answer that question, we build a logistic 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 at levels of 5% or below. Coefficients of the model can be found in table 5.

Table 5: Determinants of the sensitivity to the energy label

	Binary dependent variable:
	Sensitivity to the Energy Label
Gender: Woman	-0.481^{***}
	(0.093)
Landowner	0.270^{**}
	(0.098)
Time since last real estate research	-0.010^{*}
	(0.004)
Constant	1.324^{***}
	(0.099)
Observations	2,609
Log Likelihood	−1,434.962
Akaike Inf. Crit.	2,877.9
Note:	*p<0.05; **p<0.01; ***p<0.001

Three individual characteristics are significant to the energy labels' sensitivity: gender, landowner-tenant status and the time since the subject has conducted his last research for a piece of real estate. 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 sensitivity to energy labels; in appendix A.4 we mention the list of all control variables used in the regression. Among the three characteristics significant, a first small effect is linked to the memory. When subjects have not been facing the real estate market recently, they are less sensitive to the energy labels, a result which was expected as houses energy labels have been introduced a decade ago in France. The effect of the landowner status (in comparison to the tenant status) is interesting and much stronger: subjects being landowners of their home were more sensitive to the energy label. This effect advocates for a "patrimonial value" vision of energy efficiency for French households rather than a "value in use" vision: indeed no matter if you are tenant and landowner, you have to pay for your energy bill.

The most significant variable is not one of those previously mentioned, but gender. This characteristic is significant at a level of 0.1% and below. Its coefficient is also the most significant one. 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 subjects insensitive to the energy label. While differences in genders behaviors has been well documented in the academic literature, like in ethics, risk-aversion, trust, competitiveness, interpretation of such differences in sensitivity to green labels has not yet been reported in the literature as far as we know, and is not self-evident. Roots of differences in genders' psychology has 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 ows 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 tending 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: indeed this difference in information processing between genders arises when the volume of information to process is important and when the different informations to process are not presented in the same format, with different levels of accessibility and saliency. This is consistent with real estate ads, which exhibit both informations highly available to the public (such as price, living area and location which are in the title, pictures of the house or flat, and the energy efficiency label with colors) and informations less available (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 sensitivity 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 it. Secondly, the information design is directed to a comparative analysis (the dwelling is situated on a scale of energy performance), which has been found to increase males involvement, whereas females have been found to be comparatively less favorable 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. But beyond the sensitivity to this informational tool, we want to analyze how subjects' cognitive systems "digest" it once they have accepted this information.

4.3 Econometric analysis of labels reading

In order to understand energy labels reading by subjects sensitive 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.

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

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

A strength of these beta-regressions is that parameters μ and Φ 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 heteroscedasticity 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 homoscedasticity.

We implement the beta regressions proposed by Cribari-Neto and Zeileis (2010) in a ascendant stepwise applied to our two groups of subjects, isolated thanks to the previous section. First group gathers subjects who either were not facing a real estate ad displaying an energy label and subjects who faced an energy label but did not select this information: we call that first group "virgin subjects". The second group gathers subjects who did face an energy label and selected this information : we call them "informed subjects". The first group counts 1032 subjects, the second group counts 1968 subjects. Tables 6 and 7 present beta regression results for two different levels of type I errors in the selection of explanatory variables: 1% and 5%. Control variables are the ones used in the previous section and presented in the table 8 (see appendix A.4).

4.3.2 Energy labels perception

Table 6 presents regressors selected for their significance in the mean model for virgin subjects. No significant variables were found for the precision model applied to virgin subjects. In the model with a 1% level of significance, only one variable exhibits a significant impact on subjects rating of the house energy performance: education level of the subject. As expected following the analysis of table 4, labels have no significant impact on subjects' ratings. Education level has an impact in both extreme cases: 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 an education level below the baccalaureate tend to rate the energy performance higher. Moderate higher education levels (e.g. bachelor levels) do not exhibit a significant impact on energy ratings. If this variable is significant at the level of 1%, one should note the low pseudo-R^2 of the model, at 2.8%. When we accept type I errors at a level higher, 5%, a second variable is introduced to the model: the climate indicator. The climate indicator, depending on the department where subjects live, corresponds to the annual need for heating due to the climate. When subjects live in departments colder, they tend to slightly lower their rating of the energy quality of the house compared to average subjects. However the explanatory power of this model is still quite low when authorizing those 5% levels of significance: pseudo-R^2 is evaluated at 3.3%. These two effects are then not sufficient to explain the centered normal distribution of energy performance ratings made by "label virgin" subjects (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, the informations about heating system and windows) and infer them differently according to their prior beliefs.

Table 6: Factors influencing the mean of energy ratings for virgin subjects

	Dependent variable: House energy rating, Mean model	
	Mean model with 1% error	Mean model with 5% error
Education level:		
Below baccalaureate (CAP, BEP)	0.156^{**}	0.162^{**}
	(0.072)	(0.071)
Baccalaureate	Reference	Reference
Baccalaureate + 2 years (BTS, DUT)	-0.094	-0.091
	(0.072)	(0.072)
Baccalaureate + 3 years (Licence)	-0.133	-0.124
	(0.081)	(0.081)
Baccalaureate + 5 years and more (Master, PhD)	-0.225^{***}	-0.221^{***}
	(0.074)	(0.073)
Climate indicator		-0.000006^{**}
		(0.000002)
Constant	-0.094^{*}	0.233^{*}
	(0.050)	(0.140)
Observations	1,032	1,032
Pseudo-R^2	0.028	0.033
Log Likelihood	269.207	272.327
Note:	*p<0.1; **p<0.05; ***p<0.01	

The same procedure is applied to subjects exposed to an energy label and sensitive to it. Results are reported in table 7. For a significance level of 1%, the only variable which is now significant is the label displayed on the ad, both for the mean and the precision model, the reference label being the central one "Label D". Pseudo-R^2 of this model is much higher, at 20.5%. When significance level is set at 5%, the age of the subject and the time since he last looked for housing are introduced in the mean model. 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.

Firstly, labels are efficient in making subjects' perception unbiased. Variables which were influencing the mean of energy ratings for virgin subjects (see table 6) are cleared out for informed subjects; indeed in table 7 labels are the only variables selected in the model with a 1% significance, both for the mean and for the precision, whereas the ed-

Table 7: Factors influencing mean and precision of energy ratings for informed subjects

	Dependent variable: House energy rating, Mean & Precision Model			
	Model with 1% error		Model with 5% error	
	Mean model	Precision model	Mean model	Precision model
Label A	0.507^{***}	-1.350^{***}	0.524^{***}	-1.379^{***}
	(0.084)	(0.107)	(0.062)	(0.107)
Label B	0.532^{***}	-0.353^{***}	0.536^{***}	-0.381^{***}
	(0.068)	(0.110)	(0.067)	(0.110)
Label C	0.229^{***}	0.033	0.223^{***}	0.031
	(0.061)	(0.111)	(0.061)	(0.111)
Label D	Reference	Reference	Reference	Reference
Label E	-0.387^{***}	-0.314^{***}	-0.391^{***}	-0.342^{***}
	(0.070)	(0.113)	(0.069)	(0.114)
Label F	-0.532^{***}	-1.004^{***}	-0.530^{***}	-1.023^{***}
	(0.078)	(0.107)	(0.077)	(0.107)
Label G	-0.722^{***}	-1.204^{***}	-0.720^{***}	-1.220^{***}
	(0.087)	(0.111)	(0.086)	(0.111)
Age category:				
18-24 years old			0.113	
			(0.077)	
25-34 years old			Reference	
35-49 years old			-0.208^{**}	
			(0.063)	
50-64 years old			-0.098	
			(0.065)	
Over 65 years old			-0.095	
			(0.072)	
Time since last real estate research			0.005^{**}	
			(0.002)	
Constant	-0.136^{***}	1.846^{***}	-0.103^{*}	1.878^{***}
	(0.045)	(0.080)	(0.062)	(0.080)
Observations	1,968		1,968	
Pseudo-R^2	0.205		0.213	
Log Likelihood	454.487		467.877	

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

ucation level had an influence for virgin subjects. Besides, in the 5% significance model, two other variables are selected, but not those which were significant for virgin subjects. 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, if the model authorizing type I errors at a 1% level does not find a significant impact of individual characteristics, model with type I errors at a 5% level 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. Indeed the only age category which differs from the others are subjects between 35 and 49 years old. This category tends to rate lower the energy quality of the dwelling when an energy label is displayed. We develop a potential explanation of this effect: as these certificates were introduced in France in 2007, the 35-49 years old generation is the one most confronted to energy labels. Household of this generation have faced them in their first acquisition of a house or an apartment. 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.

However, econometric results point out a specific perception of the top-graded EPC, obvious at all significance levels. Given the proximity of label A and label B 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 model, while remaining strongly significantly different in the precision model. This is the third insight of our econometric analysis of labels reading: if labels A and B are perceived differently by subjects, in terms of mean label A perception is not better than 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. Reasons driving this "distrust" in top label are not self-evident and still have to be investigated in further research. This is a very important result when addressing the question of buildings' green value: if households do not perceive houses labelled A as more performant than houses labelled B, then it prevents houses labelled A 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 home energy labels on the perception of energy perception.

Our findings evidence that a large part of the population, although a minority, could be ignoring energy labels displayed on real estate adverts. Gender seems to have on influence on this diverse sensitivity to energy labels, which can be explained by the conjunction of both the specific design of energy performance certificates and the presentation context.

We use a specific econometric strategy based on beta regressions to understand labels reading. We show that perception is bayesian, unbiased, and consistent with the label design: each level of the energy certificate is perceived differently and gradually. However prior beliefs and idiosyncratic features of subjects interfere with the label information, triggering dispersion in subjects' judgments on energy quality for a same house. The case of the top-level label, corresponding to low-consumption houses, shows up with a higher dispersion of subjects' judgements.

Energy performance certificates are then an efficient tool to enable the discrimination of buildings according to their energy quality. They address the market failure of information asymmetry and imperfection digging the energy-efficiency gap, but they still suffer from behavioral failures. This article approach is novel by treating information as continuous: subjects are not perfectly informed or totally ignorant, they have a signal which is imperfectly 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, and highlight the top quality label.

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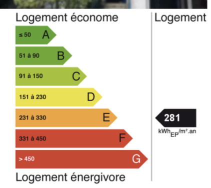
A Appendix

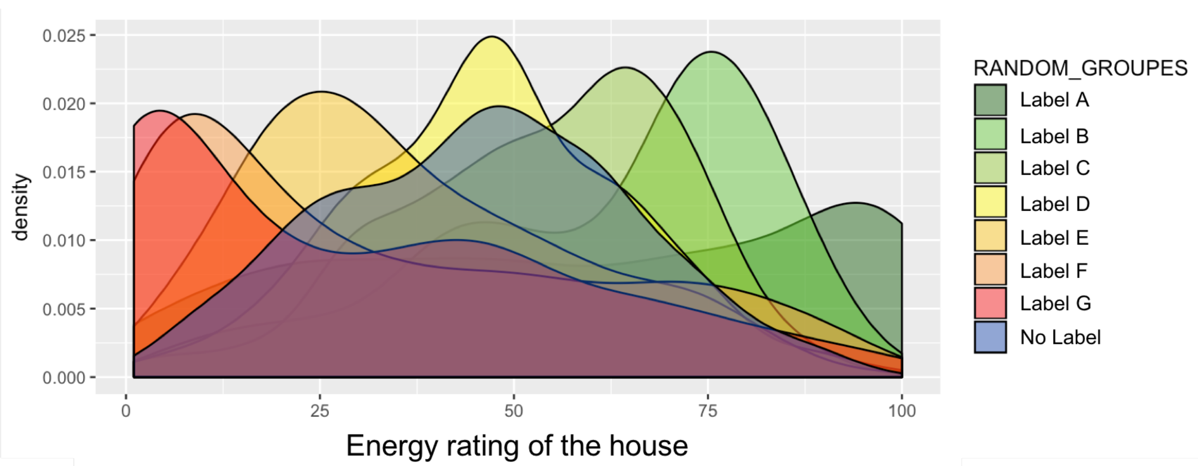
A.1 Real estate advert, Energy label E displayed

Maison 105 m², deux étages, 8 pièces, à proximité du centre-ville de Landerneau, 274 300 €

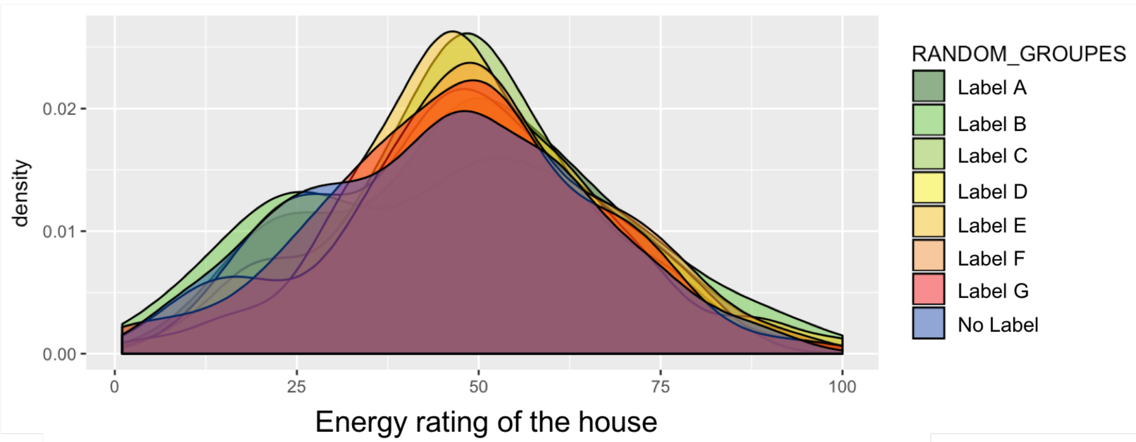
Charmante maison traditionnelle au rez-de-jardin donnant sur une ruelle piétonne. Belle pièce de vie lumineuse de 45 m², avec cheminée, exposée sud/ouest. Deux étages distribuant 4 chambres et 2 salles de bains avec WC séparés. Cuisine attenante entièrement équipée. Bureau à l'entresol. Huisseries alu double vitrage, chauffage au gaz. Garage et possibilité d'achat d'un terrain de 950 m².



A.2 Distributions of energy ratings, subjects sensitive to energy labels and subjects in control group



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



A.4 Control variables

Table 8: Control 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
Time since last real estate research
Individual/Collective heating status
Heating energy

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